Attachment 72

UNITED STATES DISTRICT COURT
WESTERN DISTRICT OF WASHINGTON
AT SEATTLE

FEDERAL TRADE COMMISSION, Plaintiff, v. AMAZON.COM, INC., a corporation; NEIL LINDSAY, individually and as an officer of AMAZON.COM, INC.; RUSSELL GRANDINETTI, individually and as an officer of AMAZON.COM, INC.; and JAMIL GHANI, individually and as an officer ofAMAZON.COM, INC., Defendants.	**Civil Action No. 2:23-cv-0932-JHC**

EXPERT REPORT OF NEALE MAHONEY

March 24, 2025

Table of contents

List of figures

I. Introduction

I.A. Experience and qualifications

(1) I am a Professor of Economics at Stanford University and the Trione Director of the Stanford Institute for Economic Policy Research (SIEPR). I am also a Research Associate at the National Bureau of Economic Research (NBER), and an Affiliated Professor at J-PAL, and the George P. Shultz Fellow at SIEPR. In 2022–2023, I was a Special Policy Advisor for Economic Policy in the White House National Economic Council.

(2) I received my PhD and MA in Economics from Stanford University in 2011 and my Sc.B in Applied Mathematics-Economics from Brown University, summa cum laude, in 2005. Before joining Stanford, I was Professor of Economics and David G. Booth Faculty Fellow at the University of Chicago Booth School of Business. I was also a Robert Wood Johnson Fellow in health policy research at Harvard University in 2011–2012.

(3) I have taught courses in Public Economics (PhD level), Industrial Organization (PhD level), Health Economics (PhD level), and Competitive Strategy (MBA level) at Stanford and Chicago Booth. My PhD teaching covers both theoretical and empirical methods (data analysis). I have published extensively in peer-reviewed academic journals on topics concerning public economics, consumer finance, health economics, industrial organization, and behavioral economics. I have served as a Co-Editor of the *American Economic Journal: Applied Economics*. Most relevant to this matter is my recent research on the difficulties consumers have cancelling subscription plans, along with my research on behavioral economics and research that examines product choice and product use in consumer markets.[1]

(4) I was a member of the Consumer Financial Protection Bureau (CFPB) Academic Research Council and am the Chair of California's Independent Consumer Fuels Advisory Committee. I received the ASHEcon Medal in 2021 (given to an economist age 40 or under who has made the most significant contributions to the field of health economics) and was a Sloan Research Fellow in 2016.

(5) My curriculum vitae is Appendix A to this report. It contains additional information about my professional experience, including my publications.

[1] Liran Einav, Benjamin Klopack, and Neale Mahoney, "Selling Subscriptions," *National Bureau of Economic Research*, No. w31547, (2023); M. Kate Bundorf, Jonathan Levin, and Neale Mahoney, "Pricing and Welfare in Health Plan Choice," *American Economic Review* 102, no. 7 (2012): 3214–48.

(6) A staff of PhD economists, economic analysts, and others at the consulting firm Bates White Economic Consulting assisted me on this matter. I directed the activities of the team, made all final decisions concerning the analytic methods and their implementation, and prepared this report.

(7) My bill rate on this engagement is $900 per hour. I also receive compensation from Bates White based on its collected staff billings for its support of me in this matter. Neither Bates White's nor my compensation is contingent on my opinions in or the outcome of this case.

I.B. Assignment

(8) I have been retained by the Federal Trade Commission (FTC) in connection with the above-captioned litigation.

(9) The FTC's Amended Complaint alleges that Amazon did not clearly and conspicuously disclose Prime's auto-renewal and price—or, in many cases, the fact that consumers were enrolling in Prime at all—prior to obtaining consumers' billing information and enrolling them in Prime.[2] The Amended Complaint also alleges that, in many instances, Amazon users became Prime members and/or were subject to Prime auto-renewal without their consent. The Amended Complaint also alleges that Amazon failed to provide consumers with simple mechanisms to cancel their Prime subscriptions.

(10) The FTC asked me to review materials and data related to Amazon's Prime enrollment and cancellation practices and opine on the following:

1. Whether Amazon's Cancellation Survey provides a reliable basis from which to draw inferences regarding the behavior of its customers;
2. The extent to which customers were unintentionally enrolled in Amazon Prime, and how much such consumers paid to Amazon in Prime membership fees during their memberships; and
3. The extent to which customers attempted to cancel their Amazon Prime memberships and believed that they had done so but did not in fact complete the cancellation process, as well as how much such customers subsequently paid to Amazon in Prime membership fees.

(11) The FTC has asked that I limit the unintentional enrollment calculations to three specific signup methods: Universal Prime Decision Page ("UPDP"), Shipping Option Select Page ("SOSP"), and Single Page Checkout ("SPC"). The FTC asked that I perform certain additional calculations of total Prime monthly fee payments by specified categories of subscribers and for alternative cut-off dates and criteria for inclusion of payments. The FTC also asked that I perform calculations of the number

[2] Amended Complaint for Permanent Injunction, Civil Penalties, Monetary Relief, and Other Equitable Relief, *Federal Trade Commission v. Amazon.com, et al.*, No: 2:23-cv-00932-JHC (W.D. Wash. September 20, 2023), Dkt. #69 (hereinafter "Amended Complaint").

of customers and total Prime monthly fees payments for several categories of subscribers that entered the cancellation process but did not successfully cancel.

(12) The FTC also asked me to review the report of Amazon's expert Dr. Ran Kivetz and, as relevant, to respond to Dr. Kivetz's opinions related to Amazon's Cancellation Survey.[3]

(13) The opinions presented in this report are based on the information available to me as of the date of this report. I reserve the right to supplement or modify my opinions if new information becomes available. I also reserve the right to respond to any additional report(s) or opinions offered by experts for Defendants.

I.C. Summary of opinions

(14) In this report I analyze the impact of aspects of Amazon's interface design on unintended enrollments to Amazon Prime and unsuccessful cancellations of Amazon Prime enrollments. Separately, for unintended enrollments and for unsuccessful cancellations, I calculate harm from Amazon's practices, using data from Amazon's Cancellation Survey as well as other Amazon customer data. I also review and rebut arguments made by Dr. Ran Kivetz concerning his assertion that Amazon's Cancellation Survey is "completely uninformative, unscientific, and unreliable with respect to whether (and how many) customers in fact unintentionally signed up for Prime."[4]

(15) With respect to harm from unintended enrollments due to Amazon's "upsell" practices, I find that:

- Amazon's Cancellation Survey provides a reliable basis to conclude that a substantial number of Amazon Prime enrollees did not intend to enroll in Amazon Prime. Amazon used the Survey in the ordinary course of business to "gather qualitative and quantitative feedback from customers [on] why they are cancelling their Prime membership."[5] It followed standard survey practices such as random sampling and randomized ordering of answers, and gathered a large number of responses from the population of interest during the time period I analyze. Survey responses indicate that a substantial number of Amazon Prime enrollees did not intend to enroll in Amazon Prime. The reliability of the Survey is corroborated by other information, such as how Survey responses changed in response to alterations in Amazon's "upsell" practices, and the fact that those who reported on the Survey that they did not intend to enroll in Prime tended to use fewer Prime benefits.
- Approximately [redacted] Amazon subscriptions that were initiated through the three at-issue "upsells" (i.e., UPDP, SOSP, SPC) represent unintentional enrollments in Amazon Prime, leading

3 Expert Report of Dr. Ran Kivetz, February 24, 2025 (hereinafter "Kivetz Report").

4 Kivetz Report, ¶ 45.

5 *See*, *e.g.*, AMZN_00037413 at 413; Kivetz Report, ¶ 24.

to more than $840 million of harm. I use a prediction model based on a linear regression to estimate a statistical relationship between an indicator of unintentional enrollment and characteristics of a customer's subscription. I then use this model to predict the unintentional enrollment rate among Prime subscriptions that were initiated through the at-issue "upsells" and were later cancelled, and I calculate payments corresponding to these unintentional enrollments. This methodology yields more than $840 million in harm from approximately [redacted] unintentional enrollments. As a robustness check, in Appendix D, I present alternative modelling approaches, and find a similar or higher magnitude of harm using these alternatives.

(16) With respect to unsuccessful cancellations due to Amazon's cancellation interface design, I find that:

- A substantial number of consumers who entered Amazon's cancellation process did not complete their cancellation and continued to pay Prime subscription fees to Amazon. Between July 2019 and March 2023, Prime subscribers entered Amazon's "Iliad" cancellation process approximately [redacted] times. Of those entries, approximately [redacted] did not result in a completed cancellation. Among those subscribers who entered the Iliad process but did not cancel during their first entry, [redacted] percent continued to pay Prime subscription fees to Amazon after their first entry into the Iliad process (the remainder cancelled at some point after the date of entry but before the next payment date).
- Prime benefit usage patterns indicate that a substantial number of subscribers exited the cancellation process with the mistaken belief that they successfully cancelled their Prime subscription. Compared to subscribers who exited the cancellation process in a manner that indicated they likely knew they remained subscribers, other groups show a higher likelihood of not using their Prime benefits after they exit the cancellation process. This is consistent with the simple logic that subscribers would not use benefits they think they no longer have.
- Amazon Prime subscribers who mistakenly thought they had cancelled their subscription incurred approximately $124 million of harm. I use a "differences-in-differences" regression approach, common in empirical economics, to quantify economic harm from unsuccessful cancellations where subscribers believed they had cancelled. For the groups I analyze, I measure the change in the percentage of subscribers with no Prime benefit usage before and after cancellation process entry relative to the analogous change for a control group who likely understood that they continued their subscription, controlling for other factors that may affect Prime benefit usage. I estimate that between [redacted] and [redacted] percent of subscriptions in these affected groups exhibit behavior consistent with the mistaken belief of successful Prime cancellation, yielding a total of approximately $124 million of harm through this channel. (For context, my estimates of harm are substantially lower than the total amount paid by Prime subscribers—about [redacted] who entered the cancellation process and exited without cancelling and without accepting an Amazon offer to remain a Prime subscriber.)

(17) With respect to Dr. Kivetz's opinion that Amazon's Cancellation Survey is "completely uninformative" on the question of whether, and the extent to which, customers unintentionally enrolled in Prime, I conclude that:

- Dr. Kivetz's claims about Amazon's flawed design and execution of the Cancellation Survey are inconsistent with Amazon's own actions and as well as standard scientific practice. Amazon designed and used the Survey to inform decisions with material business consequences, and refined and expanded the Survey over time. Similar to my analyses of unintentional enrollment, Amazon also used the Survey results for its own "unintentional signup deep dive."[6] The Survey follows standard best practices that increase survey validity.
- Dr. Kivetz's claim that the Cancellation Survey's sample will lead to an overestimate of "did not intent to enroll" ("DNI") responses is incorrect. In fact, the Survey's sample (selecting only those who cancel their subscription through online methods) has a number of features that may lead to an *underestimate* of unintended enrollments. Dr. Kivetz's claims about overestimation from bias in Survey responses due to self-selection is refuted by data on respondents' usage patterns.
- Dr. Kivetz's assertion of bias due to the design and timing of the Cancellation Survey is unsupported and inconsistent with the Survey results. His claims of potential "memory bias" that may lead to overstated DNI responses are inconsistent with actual Survey responses, which show that respondents with a longer time lag between enrollment and cancellation are *less* likely to select a DNI response, not more. More generally, Dr. Kivetz provides no evidence of any bias and ignores potential biases that could lead the Survey to *understate* DNI responses.
- Dr. Kivetz's claim that "The Observed Rate of DNI Responses is Artificially Inflated Due to Uncontrolled Guessing" is rejected by the data. Dr. Kivetz simply makes assumptions about the amount of guessing in Survey responses and uses those "guesses" to estimate possible distortions in the data. Dr. Kivetz's guessing critique is rejected by analysis of the data, which shows that the rate of guessing is likely low.
- The data patterns identified by Dr. Kivetz that he claims "call into question an interpretation of 'DNI' as evidence of true unintentional enrollment"[7] do not support his claims. Comparing Amazon Prime satisfaction between DNI and non-DNI respondents indicates lower satisfaction among DNI respondents, which is consistent with a greater degree of unintentional enrollment. In addition, changes in DNI rates over time move together with changes in Amazon's upsells that likely affected the rate of unintentional enrollment.
- Dr. Kivetz's calculation of a maximum 0.3% likelihood of an upsell resulting in an unintentional enrollment is misleading and irrelevant to my analysis. My analysis calculates how many people who *actually enrolled* in Prime did so unintentionally, while Dr. Kivetz's figure calculates the

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6 AMZN_00041335 at 335.

7 Kivetz Report, ¶ 206.

likelihood of an *individual upsell* resulting in unintentional enrollment. Because a non-Prime Amazon customer will experience numerous upsells during their checkout process, Dr. Kivetz's calculation makes the impact of upsells appear artificially low. In any case, his claim that a low rate of unintentional enrollments is inconsistent with customers having been "deceived or misled" is illogical:[8] it is analogous to asserting that spam emails resulting in harmful fraud must not have been deceitful or misleading if the rate of successful fraud per spam email sent is low.

(18) In the balance of this report, I more fully state and explain the opinions I am offering in this matter and the bases for those opinions.

[8] Kivetz Report, ¶ 384.

II. Background

(19) In this section I provide background information related to my assignment and analysis. I first describe the Amazon Prime subscription service (Section II.AII.A), the enrollment process for Amazon Prime (Section II.B), and the cancellation process for Prime subscribers (Section II.C0). I then describe the data produced in this litigation (Section II.D) and summarize the academic literature related to consumer behavior and choice architecture (Section II.E). This background information provides context for the work I performed and my opinions.

II.A. Amazon Prime

(20) All consumers who make a purchase on Amazon's platform must create an Amazon account, which allows them, among other things, to save their shipping and billing information with Amazon for use in future shopping on the Amazon platform. Many Amazon customers are also enrolled in the Amazon Prime subscription service.[9] Prime offers consumers certain benefits for a monthly or annual fee. During the time periods relevant to this case, Amazon's monthly fee for Amazon Prime has been either $10.99 (through early 2018), $12.99 (early 2018 to early 2022), or $14.99 (early 2022 to present), with corresponding annual fees of $99, $119, and $139.[10] By default, Amazon automatically renews customers' subscriptions until they take action.

(21) Prime subscriptions provide consumers access to various shipping and non-shipping benefits.[11] Prime's shipping benefits generally include faster shipping options, like two-day, one-day, or same-day shipping, for no additional cost beyond the membership fees.[12] Prime's non-shipping benefits include, among other things, digital benefits, such as access to certain Prime Video and Amazon Music services, and shopping benefits, such as discounts and deals.

9 "Amazon Prime," Amazon, https://www.amazon.com/amazonprime.

10 *See, e.g.*, Jillian D'Onfro, "Amazon will increase the price of its annual Prime plan effective on May 11," CNBC, April 26, 2018, https://www.cnbc.com/2018/04/26/amazon-will-increase-the-price-of-its-annual-prime-plan-effective-may-1.html; Annie Palmer, "Amazon increases the price of Prime nearly 17% to $139 per year," CNBC, February 3, 2022, https://www.cnbc.com/2022/02/03/amazon-increases-the-price-of-prime-nearly-17percent-to-139-per-year.html; "Amazon Prime," Amazon, https://www.amazon.com/amazonprime.

11 *See, e.g.*, "Prime Membership Benefits," Amazon, https://www.amazon.com/b/node=23945845011; Kivetz Report, Figures C9d–C9f.

12 Consumers are required to meet purchase thresholds for some shipping benefits—e.g., obtaining same day shipping at no additional cost requires a minimum purchase. "Prime Membership Benefits," Amazon, https://www.amazon.com/b/node=23945845011.

(22) Based on the data Amazon produced in this litigation, Prime subscribers primarily used the following shipping and non-shipping benefits (limited to types of benefits that are only available to Prime subscribers):[13]

Figure 1: Usage of Prime shipping benefits, by type [redacted] sample)

Shipping type	2018	2019	2020	2021	2022	2023*
2-DAY	[redacted]					
1-DAY						
3-5 DAY						
6-10 DAYS						
Others						

* 2023 data are partial-year data through June 2023.

Figure 2: Usage of Prime non-shipping benefits, by type [redacted] sample)

Benefit type	2018	2019	2020	2021	2022	2023*
PRIME VIDEO	[redacted]					
PRIME MUSIC						
PRIME PHOTOS						
AMAZON CHANNELS						
PANTRY ORDERS						
Others						

* 2023 data are partial-year data through June 2023.

(23) Some Prime services are similar to services that can be obtained without a Prime subscription. An example is Amazon Music. Customers without Prime can access Amazon Music Free, Amazon Music Standard, and Amazon Music, while customers with Prime can additionally access Amazon Music Prime. Although there are differences across the Prime and non-Prime services, both provide access to music and ad-free top podcasts.[14] Another example is Prime Video, through which "Customers are able to purchase or rent a selection of titles from the Prime Video catalog, without needing an Amazon Prime or Prime Video membership."[15] Similarly, customers without a Prime subscription can receive free shipping on Amazon orders that exceed a minimum threshold of eligible items.[16] One

[13] For the purpose of analyzing Amazon Prime customer behavior, I select a random sample of [redacted] Amazon Prime customers (hereafter [redacted] sample") and use it as a representative subset of the overall Amazon Prime customer population since January 1, 2018.

[14] *See, e.g.*, "What Are the Differences Between the Amazon Music Subscriptions?," Amazon, https://www.amazon.com/gp/help/customer/display.html?nodeId=GW3PHAUCZM8L7W9L.

[15] *See, e.g.*, "Do I Need an Amazon Prime Membership to Use Prime Video?," Amazon, https://www.amazon.com/gp/help/customer/display.html?ref_=hp_left_v4_sib&nodeId=GZCHXL8CUW3VWJQP ("You do not need to have an Amazon Prime membership to use Prime Video. Customers are able to purchase or rent a selection of titles from the Prime Video catalog, without needing an Amazon Prime or Prime Video membership. Purchases from the Prime Video Store are automatically charged to your 1-Click payment method.").

[16] *See, e.g.*, "Free Shipping by Amazon," Amazon, https://www.amazon.com/gp/help/customer/display.html?nodeId=%0bGZXW7X6AKTHNUP6H.

implication of this overlap is that some or many consumers who use such services may not know whether they are using benefits only provided to Prime subscribers.[17]

II.B. Subscribing to Amazon Prime

(24) Consumers can subscribe to Prime in multiple ways. Almost half of consumers subscribe to Prime in the course of purchasing a product through Amazon's e-commerce platform. In a standard purchasing flow, a consumer finds products they want to buy, adds them to their online cart, and then checks out by entering billing and shipping information (if not already provided). During the checkout process for non-Prime consumers, however, Amazon diverts consumers from this process by presenting one or more offers to subscribe to Prime—"upsells"—before they can complete their purchase.

(25) Amazon offered Prime upsells to customers as part of its "Multi-Page Pipeline" (prior to fall 2022) or "TrueSPC" (starting in fall 2022) product checkout user flows.[18] In the Multi-Page Pipeline, customers without saved billing and address "defaults" saw the SOSP upsell, at least until that upsell was suppressed and then deprecated, starting in 2021.[19] Customers who accepted an SOSP offer then saw the Shipping Option Select Page Prime Decision Page (SOSP PDP) variation of UPDP. Consumers who did not accept an SOSP upsell saw the UPDP upsell. My understanding is that over time, Amazon had different rules about how frequently customers were shown UPDP—e.g., if customers bought products multiple times in the same day or week, they might nevertheless only be shown the UPDP [redacted] per day or [redacted] per week. If a customer had not accepted an earlier upsell, they then received additional Prime upsells on the product-checkout (SPC) page. In the "TrueSPC" product checkout user flow, SOSP upsells did not exist. Also, in TrueSPC, only customers who had saved "default" billing information were shown the UPDP page, again based on rules regarding how frequently Amazon displayed the UPDP page to individual customers. If a customer had not accepted an earlier upsell, they then received additional Prime upsells on the new version of the SPC product checkout page, which maintained the upsells from the Multi-Page Pipeline version of SPC and added additional upsells for some customers.[20]

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17 Amazon's customer data show that Prime subscribers use benefit types which are available to non-Prime subscribers. In addition, a given benefit is sometimes categorized as a Prime benefit in one month and a non-Prime benefit in another. The top five most commonly used non-Prime benefits are [redacted] (these benefits can be obtained by non-Prime members with orders that exceed a minimum threshold of eligible items). *See* footnote 16.

18 AMZN-PRM-FTC-002111339 at 362.

19 AMZN-PRM-FTC-000348598.

20 *See, e.g.*, AMZN-PRM-FTC-002111339 at 362–363.

(26) Between May 2017 and June 2023, Amazon presented three types of Prime upsells as a standard component of the checkout process for non-Prime customers:[21]

1. The Universal Prime Decision Page ("UPDP") upsell.[22] Amazon presents the UPDP to non-Prime consumers during the checkout process. Consumers cannot avoid the UPDP, meaning they cannot complete the checkout process for their purchase without either accepting or declining Prime. If a consumer accepts, Amazon subscribes them to Prime even if the consumer later abandons their cart without completing the purchase.
2. The Shipping Option Select Page ("SOSP") upsell.[23] Consumers who encountered the SOSP during the checkout process were required to select a shipping option on the page. The SOSP presented free expedited shipping with Prime as one delivery option. Consumers who selected this option were then shown a variation—sometimes referred to within Amazon as the SOSP PDP—of the UPDP page. If a consumer accepted the SOSP PDP offer, Amazon subscribed them to Prime even if the consumer later abandoned their cart without completing the purchase.
3. The Single Page Checkout ("SPC") and True Single Page Checkout ("TrueSPC") upsells.[24] The SPC was the final page consumers complete during the checkout process. The SPC included two Prime offers: a button offering free expedited shipping with Prime (similar to the SOSP upsell) and a banner offering the same. Amazon subscribed any consumer who selected one of these options to Prime if they completed the checkout process. Amazon replaced SPC with "TrueSPC" around October 2022.[25] The TrueSPC page maintains the two SPC upsell offers and adds additional Prime upsell offers for some consumers.

(27) Figure 3 through Figure 5 show sample screenshots from each of these three types of upsells as viewed on a desktop computer. Amazon generally presents similar Prime subscription upsells on both mobile and desktop devices.[26]

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21 *See, e.g.*, Kivetz Report, ¶ 236; Amazon's Second Supplemental Objections & Responses to FTC's First Set of Interrogatories (May 3, 2024) (hereinafter "Amazon's May 3, 2024 Objections & Responses to the FTC's First Set of Interrogatories"), pp. 7–30. I understand that Dr. Marshini Chetty, also retained by the FTC in this matter, has opined on the design of the three upsells. Expert Report of Marshini Chetty, Ph.D., February 24, 2025 (hereinafter "Chetty Report").

22 Amazon's Supplemental Objections & Responses to FTC's First Set of Interrogatories (April 10, 2024) (hereinafter "Amazon's April 10, 2024 Objections & Responses to the FTC's First Set of Interrogatories"), pp. 10–11.

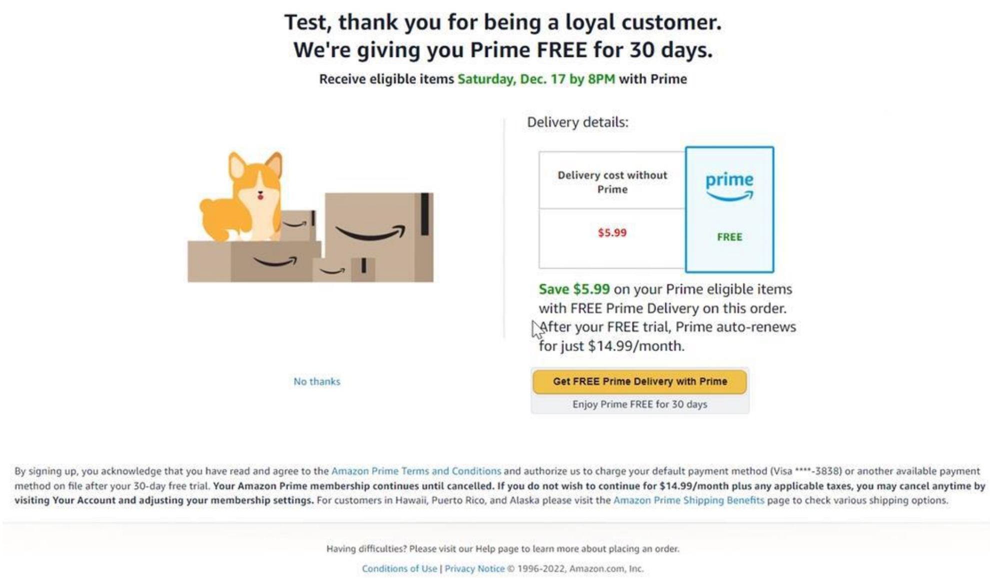
23 Amazon's April 10, 2024 Objections & Responses to the FTC's First Set of Interrogatories, pp. 15–16, 26–28.

24 Amazon's April 10, 2024 Objections & Responses to the FTC's First Set of Interrogatories, pp. 11–14, 23–25; Amazon's Written Objections & Responses to FTC's Notice of Rule 30(b)(6) Deposition of Amazon (February 13, 2025) (hereinafter "Amazon's February 13, 2025 Objections & Responses to the FTC's 30(b)(6) Notice"), pp. 31–32.

25 Amended Complaint, ¶ 63.

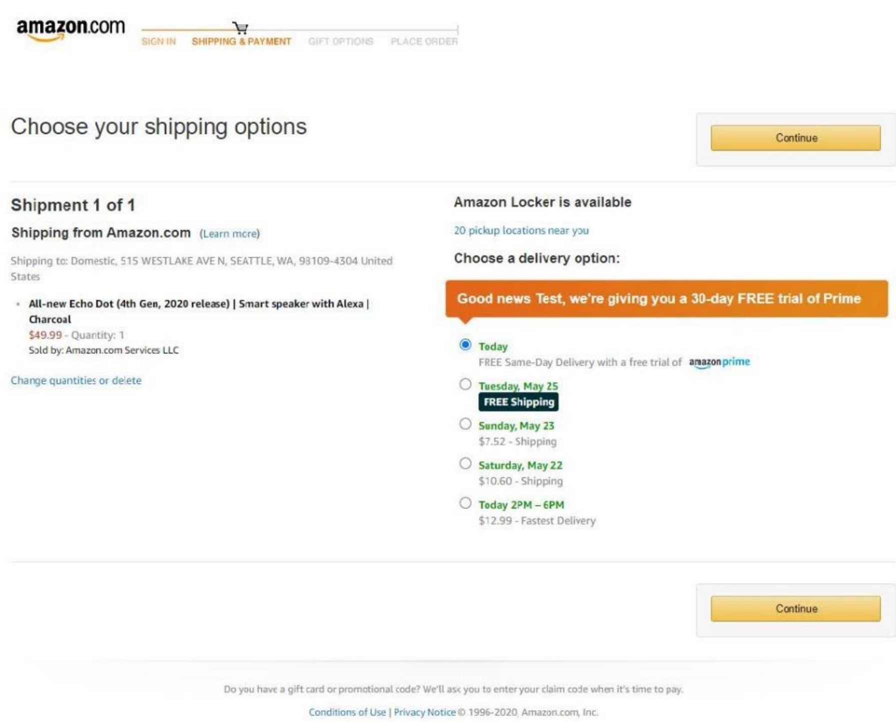
26 Amazon's April 10, 2024 Objections & Responses to the FTC's First Set of Interrogatories, pp. 17–19, 28–30.

Figure 3: UPDP upsell screenshot



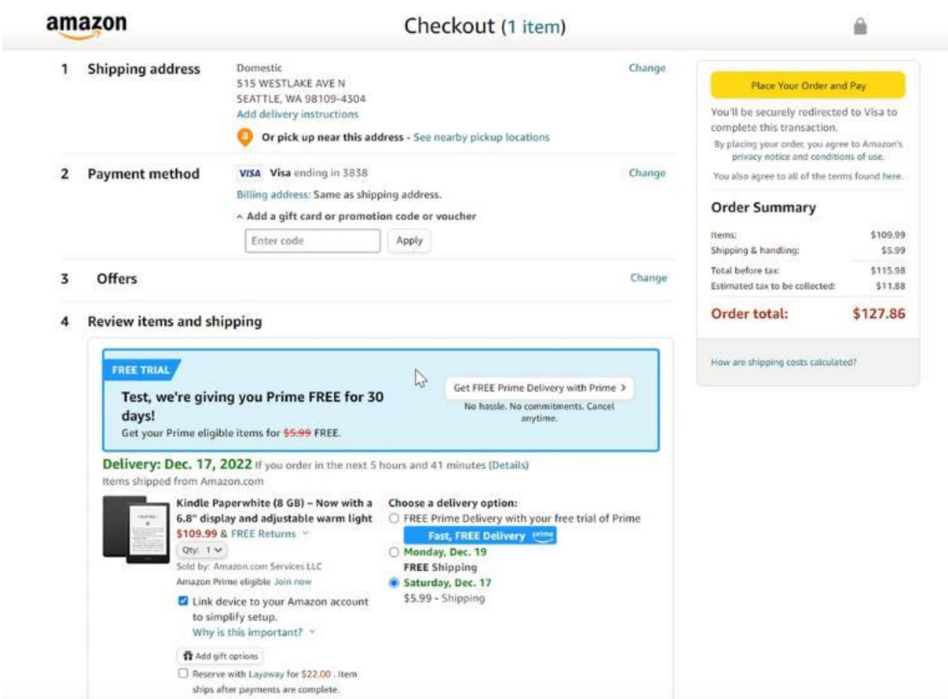
Source: Amazon's May 3, 2024 Objections & Responses to the FTC's First Set of Interrogatories, p. 10.

Figure 4: SOSP upsell screenshot



Source: Amazon's May 3, 2024 Objections & Responses to the FTC's First Set of Interrogatories, p. 15.

Figure 5: SPC upsell screenshot



Source: Amazon's May 3, 2024 Objections & Responses to the FTC's First Set of Interrogatories, p. 12.

(28) Many consumers who subscribe to Prime, whether intentionally or not, through one of these upsells start their subscription with a free trial. After the free trial ends, Amazon begins charging a monthly fee, using the consumers' stored billing information, and continues to charge subscription fees until consumers take an action. Amazon charges consumers who start with a "hard offer" or "paid trial"—as opposed to a free trial—immediately upon enrollment, and continues to charge such consumers until the consumer cancels.

(29) Consumers can also subscribe to Prime by other methods, such as visiting www.amazon.com/prime ("Slashprime") and providing the required personal and payment information. Methods like Slashprime are distinct from an "upsell" in that the option to join Prime does not arise as part of the checkout process.

(30) Together, UPDP, SOSP, and SPC accounted for between [redacted] and [redacted] of Prime subscriptions each year from January 2018 to June 2023 and [redacted] of Prime subscriptions for the full period. *See* Figure 6.

Figure 6: Prime subscriptions by method, January 2018 to June 2023

Signup method	Proportion of overall Prime subscriptions					
	2018	2019	2020	2021	2022	2023*
UPDP	[redacted]					
SOSP						
SPC						
Others						

* 2023 data are partial-year data through June 2023.

(31) Consumers who signed up through the UPDP, SOSP, and SPC primarily signed up via either a desktop or mobile device, as shown in Figure 7.

Figure 7: Prime subscriptions by signup method and device type, January 2018 to June 2023

Signup method	Signup device	Proportion of subscriptions					
		2018	2019	2020	2021	2022	2023*
UPDP	Desktop	[redacted]					
	Mobile						
	Other						
SOSP	Desktop						
	Mobile						
	Other						
SPC	Desktop						
	Mobile						
	Other						

* 2023 data are partial-year data through June 2023.

(32) For the purposes of my analysis, I define "unintentional enrollee" to mean any Amazon consumer who subscribes to Prime without knowing or understanding they were doing so.

II.C. Cancelling Amazon Prime

(33) Consumers can cancel their Prime subscriptions through the online process described below or by contacting Amazon's customer service. One Amazon document indicates that, as of July 2019, fewer than [redacted]% of Prime cancellations were made through subscribers contacting customer service.[27]

(34) To cancel online, Prime subscribers must complete multiple steps. For example, a subscriber could start the cancellation process as follows: first locate the "End Membership" option, which subscribers can find by clicking through several pages and options (e.g., select "Accounts & Lists" to get a

27 *See* AMZN_00021537 at 537; Kivetz Report, ¶ 25.

dropdown menu, then click on "Prime Membership," then click on "Manage Membership," then click on "End Membership").[28] Clicking "End Membership," however, does not end membership. Consumers must next navigate a multi-page process to complete cancellation. Amazon internally referred to its online cancellation process as the "Iliad."[29]

(35) I understand that, until around March 30, 2023, the Iliad cancellation process worked as follows:[30]

- After a consumer located and clicked "End Membership," Amazon presented additional pages that contain multiple links and options.
- In the first step, Amazon directed these consumers to the "Marketing Page." This page contained links and details about Prime benefits and showed three buttons at the bottom: (i) Remind Me Later, (ii) Continue To Cancel, and (iii) Keep My Benefits. Figure 8 presents a screenshot of the Iliad Marketing Page as seen on desktop devices.
    A. The Remind Me Later button had additional text stating, "Keep my benefits and remind me 3 days before my membership renews" or just "Remind me 3 days before my membership renews."[31] Clicking this button ended the cancellation process—without cancellation—and took consumers to the Prime Central or Membership Central Page.
    B. Clicking the Continue To Cancel button took consumers to the next page of the cancellation process, but did not result in cancellation without further clicks.
    C. The Keep My Benefits button also ended the process without cancellation and took consumers to the Prime Central or Membership Central Page.
- Amazon next directed consumers who clicked Continue To Cancel on the Marketing Page to the "Offer Page," which provided consumers the option to switch to a different Prime plan (*e.g.*, from monthly to annual or vice versa). The Remind Me Later and Continue To Cancel buttons appeared at the bottom of the Offer Page, along with a Keep My Membership button, as shown in Figure 9. The Keep My Membership button served the same function as the Keep My Benefits button on the Marketing Page.
- Finally, Amazon took consumers who clicked on Continue to Cancel on the Offer Page to the "Cancellation Page." In addition to the Remind Me Later and Keep My Membership buttons, the Cancellation Page contained buttons to pause membership at the end of the billing cycle ("Pause

[28] Amended Complaint, ¶¶ 131–133 & Attachment Q at 1–2.

[29] *See, e.g.*, AMZN_00009360 at 360 ("Currently, members who want to initiate cancellation can enter the self-cancel flow (known internally as 'Iliad')"); Hills Dep. Exs. 2–3 (AMZN_00001517); Kivetz Report, footnote 41.

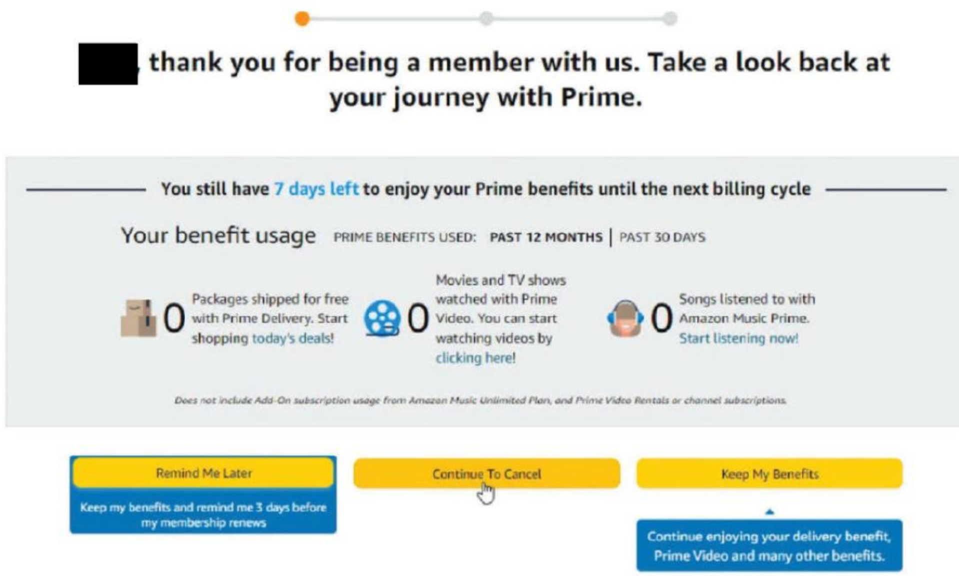
Although the record does not identify Amazon's reason for naming the cancellation process the "Iliad," the term commonly refers to an ancient Greek 24-book epic poem by Homer about the Trojan War and the siege of Troy, which lasted 10 years and ended when the Greeks used the Trojan Horse to deceive the Trojans and sack the city.

[30] See, e.g., Amended Complaint, ¶¶ 127–163; Amazon's February 13, 2025 Objections & Responses to the FTC's 30(b)(6) Notice, pp. 5–7.

[31] Amended Complaint, Attachment R at 8–9.

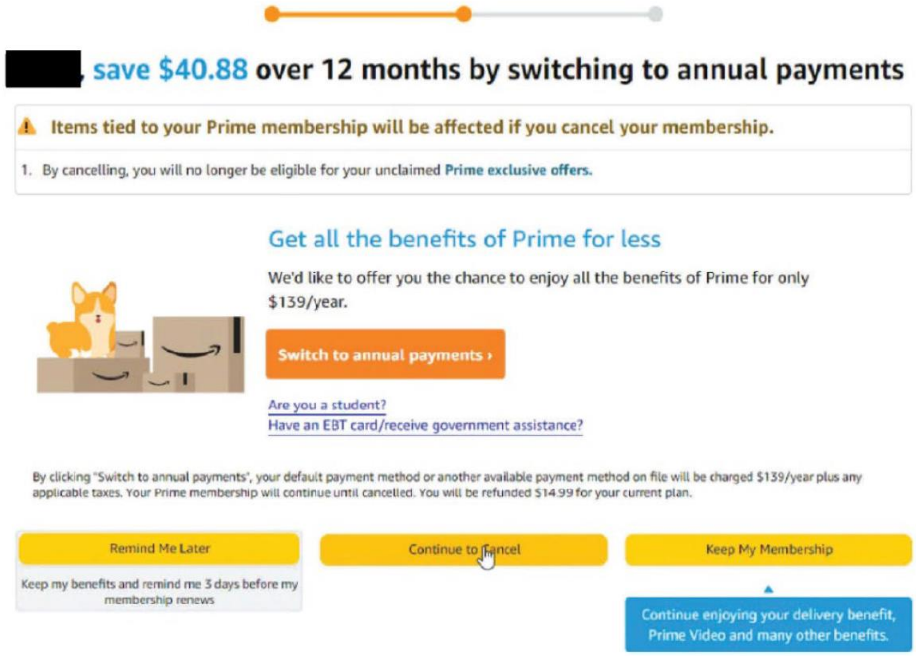
on [date]"), end membership at the end of the billing cycle ("End on [date]"), and immediately end membership ("End Now"), as shown in Figure 10.

Figure 8: Screenshot of the Iliad "Marketing Page"



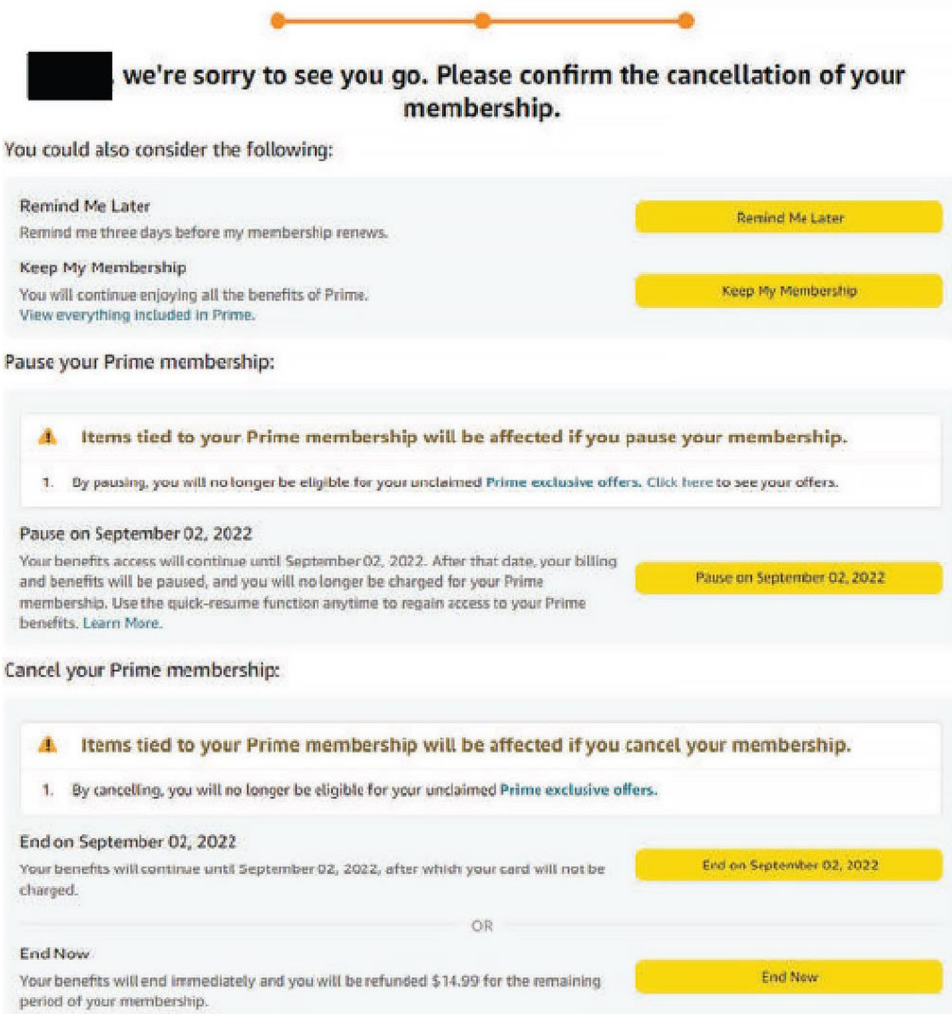
Source: Amended Complaint, Attachment Q at 3.

Figure 9: Screenshot of the Iliad "Offers Page"



Source: Amended Complaint, Attachment Q at 4.

Figure 10: Screenshot of the Iliad "Cancellation Page"



Source: Amended Complaint, Attachment Q at 5.

(36) The Iliad cancellation process is similar on both mobile and desktop devices.

(37) Around March 30, 2023, Amazon removed one step from the Iliad cancellation process and made certain other changes.[32] This updated process (which I refer to as Iliad 2.0) requires consumers to navigate pages with options largely similar to the prior process. To start the process, a consumer must first locate and click the End Membership button as described above. To complete cancellation, the consumer must then go through additional pages and steps.

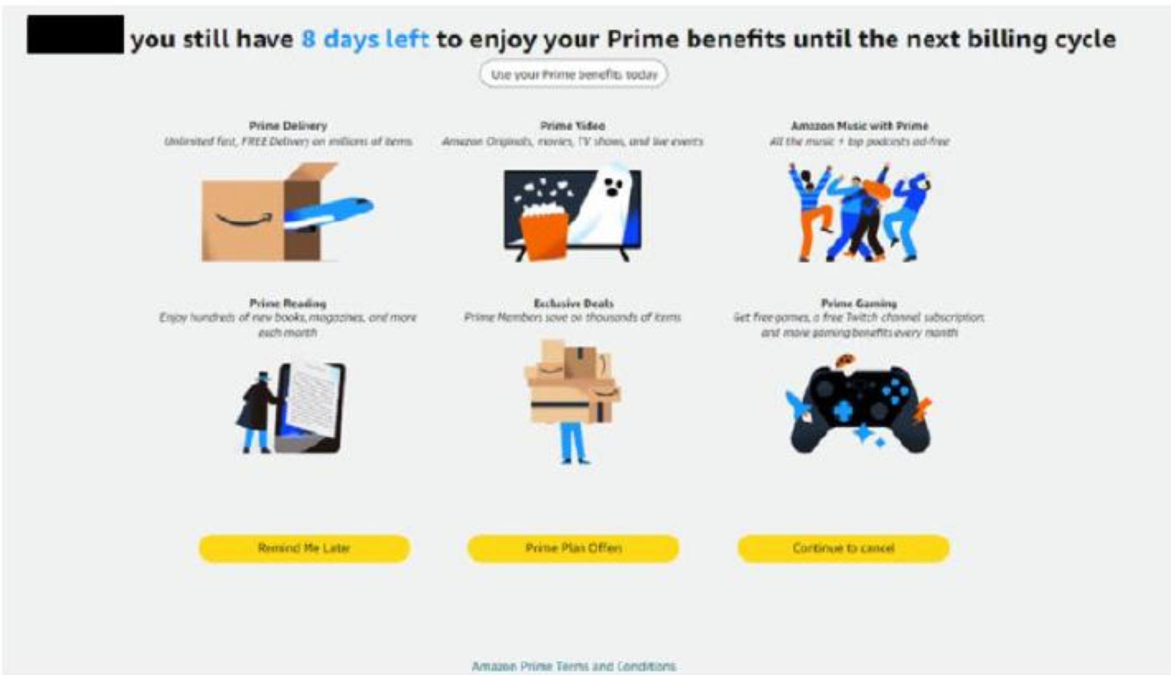
- Iliad 2.0 first directs consumers who click on "End Membership" to a page similar to the Marketing Page described above, presenting links and details about Prime benefits and showing

[32] *See, e.g.*, AMZN-PRM-FTC-000939073.

three buttons: Remind Me Later, "Prime Plan Offers" (rather than Keep My Benefits) and Continue To Cancel). See Figure 11.

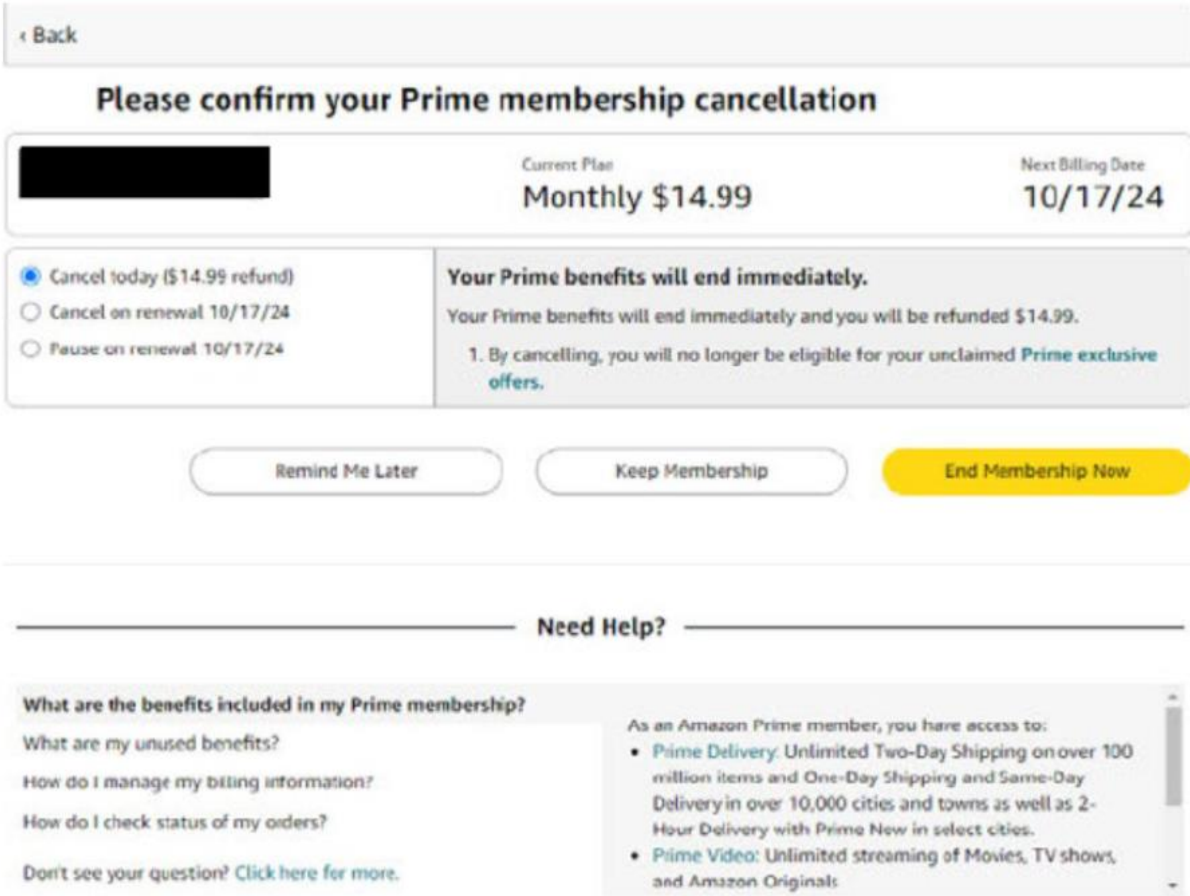
- Amazon takes consumers who click Continue To Cancel to a page similar to the Cancellation Page described above. In addition to the cancellation-related radio buttons ("Cancel today []," "Cancel on renewal []," and "Pause on renewal []"), the page presents three buttons (Remind Me Later, Keep Membership, and End Membership Now). See Figure 12.

Figure 11: Screenshot of the first page in Iliad 2.0 after subscribers click "End Membership"



Source: Chetty Report, Figure 21.

Figure 12: Screenshot of the final page in the Iliad 2.0 process



Source: Chetty Report, Figure 24.

II.D. Amazon's customer data and Cancellation Survey data

(38) Amazon produced in this litigation certain data, which Amazon described as "ordinary course data," about its customers and their Prime memberships that I use to analyze enrollment and cancellation harm.[33] Specifically, these data include customer-level information about signups, cancellations, plans, benefit usage, and Prime transactions. Each dataset includes unique customer identifiers that allow for identifying and linking customers across data sets. For example, these datasets include, among other things, the following elements:

- Signups: The date when a customer signed up for Prime, the method they used to sign up, and the type of device they used to sign up (January 2014–June 2023).

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33 Amazon's letter to FTC regarding production of certain data (July 18, 2024); Amazon's letter to FTC regarding certain materials (December 6, 2024), p. 1.

- Cancellations: The date when a customer cancelled or paused their Prime subscription (January 2018–June 2023). The data separately include information about when a customer entered the cancellation process, how far they made it through the process, and what buttons they clicked (if any) when going through the process (July 2019–June 2023).
- Plans: What type of Prime plan a customer had and for what periods of time they had that plan, as well as when they were in a billing problem or auto renew state (April 2009–June 2023).
- Benefits usage: What Prime benefits a customer used and how often (January 2014–June 2023).
- Prime transactions: Customer payments, refunds, and chargebacks for their Prime subscription (May 2017–June 2023).

(39) Amazon also produced ten datasets that contain responses from online cancellation surveys that Amazon has conducted since 2018. One of these datasets, which contains [redacted] responses from April 17, 2020 to February 5, 2024, includes customer identifiers that, by using a separate "mapping" file produced by Amazon, can be merged with the customer data.[34] Additionally, Amazon produced data that identifies customers who were shown a popup asking them to complete a cancellation survey after they completed cancelling their Prime subscription online. Unless stated otherwise, my analysis of the survey data Amazon produced in this case relies on the survey responses for which Amazon provided customer mapping information. I identified certain fields within the survey responses and other customer data that are useful for my empirical analyses, such as the start date of the Prime subscription that preceded their Survey response (i.e., the start date of the subscription that the customer cancelled before receiving the survey prompt) and related information (e.g., signup method, benefit use, subscription duration, amounts paid).

II.E. The economic literature on consumer choice and choice architecture

(40) Substantial economic research supports the proposition that consumers may take actions that do not reflect their underlying preferences due to a combination of their cognitive constraints and how decisions are framed for them, with the latter often being referred to as the "choice architecture" they face.[35] One important implication of this research for the current matter is that even seemingly small changes in how Amazon presents its Prime enrollment and cancellation options to consumers can potentially have a substantial impact on the decisions those consumers make, and can induce them to make decisions that are against their own preferences. In Section III and Section IV, I empirically

[34] The file "responseid_CIDv2" in Amazon's production links survey response identifiers to the field *customer_id_hashed* identifying customers in other datasets. The file "SV_0OInYvHGGzsKsBf" in AMZN-PRM-FTC-DATA-00000017 contains the raw data for the Cancellation Survey for which Amazon provided mapping information.

[35] *See, e.g.*, Richard H. Thaler, Cass R. Sunstein, and John P. Balz, "Choice Architecture," in *The Behavioral Foundations of Public Policy*, ed. Eldar Shafir (Princeton University Press, 2014), 428–439.

estimate the impact of Amazon's interface design on consumer choices relating to Prime enrollments and cancellations. In this section, I discuss the academic literature on the underlying mechanisms. This literature supports the conclusion that the intertwining effects of cognitive constraints and choice architecture on consumer decisions can be substantial and can leave consumers worse off.

(41) A fundamental principle of behavioral economics is that consumers have limited attention, which may cause them to miss or ignore relevant information in their decision-making.[36] In addition, studies have shown that consumers generally are prone to particular biases in their decision-making, such as myopia,[37] default effects,[38] inertia (or "status-quo bias"),[39] and placement effects.[40]

(42) This combination of inattention and biases can lead to sub-optimal decisions when consumers are considering, for example, whether or not to maintain a subscription. For example, research I have conducted on replacement of credit and debit cards finds that, presumably due to inattention or inertia, consumers continue to pay for "subscriptions" even when the benefit falls below the price.[41] Other studies have found similar consumer inertia in decisions related to health club memberships and attendance.[42]

[36] *See, e.g.,* Stefano DellaVigna, "Psychology and Economics: Evidence from the Field," *Journal of Economic Literature* 47, no. 2 (June 2009): 315–372. *See also* Xavier Gabaix, "Behavioral Inattention," in *Handbook of Behavioral Economics: Applications and Foundations 1*, vol. 2, (North-Holland, 2019): 261–343.

[37] "Consumer myopia" refers to the idea that consumers tend to overweight near-term costs and benefits relative to longer-term costs and benefits. *See, e.g.,* Xavier Gabaix, "Behavioral Inattention," in *Handbook of Behavioral Economics: Applications and Foundations 1*, vol. 2, (North-Holland, 2019): 261–343.

[38] "Default effects" refers to the tendency of consumers to be influenced by which choices are presented as "default" choices—choices that are automatically made absent an active choice to the contrary. *See, e.g.,* B. Douglas Bernheim, Andrey Fradkin, and Igor Popov, "The Welfare Economics of Default Options in 401 (k) Plans," *American Economic Review* 105, no. 9 (2015): 2798–2837; B. Douglas Bernheim and Jonas Mueller-Gastell, "A General Solution to the Problem of Setting Optimal Default Options," *AEA Papers and Proceedings*, vol. 112, (2022): 131–35; Richard H. Thaler and Cass R. Sunstein, *Nudge: Improving Decisions about Health, Wealth, and Happiness* (London: Penguin, 2009): 85–89.

[39] "Status quo bias" refers to a consumer's tendency to maintain past decisions beyond the point where they would benefit from switching to a new choice. Godefroid, Plattfaut, and Niehaves (2023) survey the relevant literature and find that people prefer to avoid change and maintain the status-quo, even when it harms them: "[Status-quo bias can] affect economic decisions, which can prove to be harmful to those individuals whom the decisions affect." Marie-E. Godefroid, Ralf Plattfaut, and Björn Niehaves, "How to Measure the Status Quo Bias? A Review of Current Literature," *Management Review Quarterly* 73, no. 4 (2023): 1667–1711. *See also*, William Samuelson and Richard Zeckhauser, "Status Quo Bias in Decision Making," *Journal of Risk and Uncertainty*, 1 (1988): 7–59. One study of breakfast cereal purchases finds that households switching brands incur psychological costs equivalent to $4.33, more than every brand's price. *See* Matthew Shum, "Does Advertising Overcome Brand Loyalty? Evidence From the Breakfast-Cereals Market," *Journal of Economics and Management Strategy* 13, No. 2 (2004): 241–272.

[40] For instance, the ordering of results in online search can affect what users click on. *See* Nick Craswell, Onno Zoeter, Michael Taylor, and Bill Ramsey, "An Experimental Comparison of Click Position-Bias Models," *Proceedings of the 2008 International Conference on Web Search and Data Mining* (2008): 87–94; Eric J. Johnson, *The Elements of Choice: Why the Way we Decide Matters* (New York: Penguin, 2021): 187.

[41] Liran Einav, Benjamin Klopack, and Neale Mahoney, "Selling Subscriptions," *National Bureau of Economic Research*, no. w31547 (2023).

[42] DellaVigna and Malmendier (2006) study health club memberships and attendance, finding that consumers overestimate their future gym attendance and forfeit potential savings by making irrational choices to maintain infrequently-used

(43) Imperfections in consumer decision-making can be exacerbated by firms' choices in how to present information to consumers. Importantly, a firm wanting to discourage a particular choice need not remove that choice entirely. As one paper puts it: "there are many ways to present a choice to the decision-maker… what is chosen often depends upon how the choice is presented."[43]

(44) One recent study finds that how app downloading choices are presented to consumers can substantially impact how consumers download and use apps. For instance, decreasing the number of decision points, making choices seem to be a default, and matching common patterns found in other usual activities, can all make users more likely to download an app and enable certain features.[44] Several studies have found that various forms of "shrouded" costs such as shipping costs, future operating costs, or taxes can take advantage of consumers' inattention and/or myopia and cause them to make sub-optimal decisions due to their miscalculation of relevant costs.[45] More broadly, and in contrast to a simple neoclassical view of the world that says that having more choices must improve consumer outcomes, overly complex choices can lead to errors or inaction.[46]

(45) The interaction between consumers' inattention and cognitive biases and the relevant choice architecture on consumer decisions can give firms a potentially strong ability and incentive to manipulate consumers into making decisions against their interests.

(46) Perhaps even more straightforwardly, there is a large literature on how the existence of "switching costs" can give firms pricing power.[47] This gives firms an incentive to increase the costs of switching away from their products when they are able to do so.[48] Switching costs can, even for completely rational consumers, reduce what would otherwise be optimal switching behavior. When interacted

memberships. *See* Stefano DellaVigna and Ulrike Malmendier, "Paying Not to Go to the Gym," *American Economic Review* 96, no. 33 (2006): 694–719.

[43] Eric J. Johnson, Suzanne B. Shu, Benedict GC Dellaert, et al., "Beyond Nudges: Tools of a Choice Architecture," *Marketing Letters* 23, (2012): 487–504.

[44] Crystal Reeck, Nathaniel A. Posner, Kellen Mrkva, and Eric J. Johnson, "Nudging App Adoption: Choice Architecture Facilitates Consumer Uptake of Mobile Apps," *Journal of Marketing* 87, no. 4 (2023): 510–527.

[45] A "shrouded" attribute is any information that is hidden from a consumer or is difficult to access. *See, e.g.,* Jennifer Brown, Tanjim Hossain, and John Morgan, "Shrouded Attributes and Information Suppression: Evidence from the Field," *The Quarterly Journal of Economics* 125, no. 2 (2010): 859–876. *See also* Michael D. Grubb, "Selling to Overconfident Consumers," *American Economic Review* 99, no. 5 (2009): 1770–1807; Michael D. Grubb and Matthew Osborne, "Cellular Service Demand: Biased Beliefs, Learning, and Bill Shock," *American Economic Review* 105, no. 1 (2015): 234–271; Hunt Allcott and Nathan Wozny, "Gasoline Prices, Fuel Economy, and the Energy Paradox," *Review of Economics and Statistics* 96, no. 5 (2014): 779–795.

[46] *See, e.g.,* Barry Schwartz, *The Paradox of Choice: Why More Is Less* (New York: HarperCollins, 2004).

[47] One survey of the marketing literature on switching costs finds that product complexity, provider heterogeneity, product use, and previous switching experience significantly increase consumers' intentions to stay with their current service provider. *See* T.A. Burnham, J.K. Frels, and V. Mahajan, "Consumer switching costs: A typology, antecedents, and consequences," *J. of the Acad. Mark. Sci.* 31 (2003): 109–126.

[48] Joseph Farrell and Paul Klemperer, "Coordination and Lock-In: Competition with Switching Costs and Network Effects," in *Handbook of Industrial Organization*, ed. by Mark Armstrong and Robert H. Porter (Amsterdam: Elsevier, 2007), 3:1967–2072; Paul Klemperer, "Competition When Consumers Have Switching Costs: An Overview," *The Review of Economic Studies* 62 (4) (1995): 515–539.

with consumers' behavioral biases, such as myopia or inertia, the impact of switching costs can be magnified.

III. Harm to consumers who unintentionally enroll in Amazon Prime

(47) In this section I discuss my analysis of unintentional enrollees in Amazon Prime. First, I describe Amazon's Cancellation Survey and explain why it provides a reliable basis to draw inferences regarding the behavior of its customers (Section III.A). Second, I use a regression analysis to estimate, using conservative assumptions where necessary, unintentional enrollment among Prime subscribers (Section III.B).

III.A. Amazon's Cancellation Survey provides a reliable basis to draw inferences regarding the behavior of its customers

(48) I use data from Amazon's Cancellation Survey to analyze unintentional enrollment.

(49) Dr. Kivetz, an expert retained by Amazon, instead opines that such use of Amazon's Cancellation Survey is not appropriate. His claims are flawed for the reasons I explain in this section as well as in Section V, where I respond directly to Dr. Kivetz.

III.A.1. Amazon designed, invested in, and refined its Cancellation Survey to provide it with business intelligence about its customers

(50) Around late 2018, in a project led by Amazon's Prime Retention Team, Amazon began conducting an online Cancellation Survey of customers who cancelled their Prime subscriptions.[49] Amazon's internal documentation regarding the Cancellation Survey as of early October 2018 described the purpose of the Survey as follows: "the goal of the cancellation survey is to be able to gather qualitative and quantitative feedback from customers [on] why they are cancelling their Prime membership."[50] Another internal Amazon document from July 2019 provides more detail:

> To get more insight on why people are leaving Prime, we started including a link to a cancellation survey on the Iliad cancellation flow and on the cancellation emails so that customers can provide candid feedback… By comparing customer and usage data to the cancellation survey responses, we hope to determine a customer's likelihood of cancelling in advance and why they are likely to cancel. With this knowledge, we intend to course-correct the customer through personalized engagement and risk reduction strategies.[51]

49 *See*, *e.g.*, AMZN_00001517; Kivetz Report, ¶ 27.

50 *See*, *e.g.*, AMZN_00037413; Kivetz Report, ¶ 24.

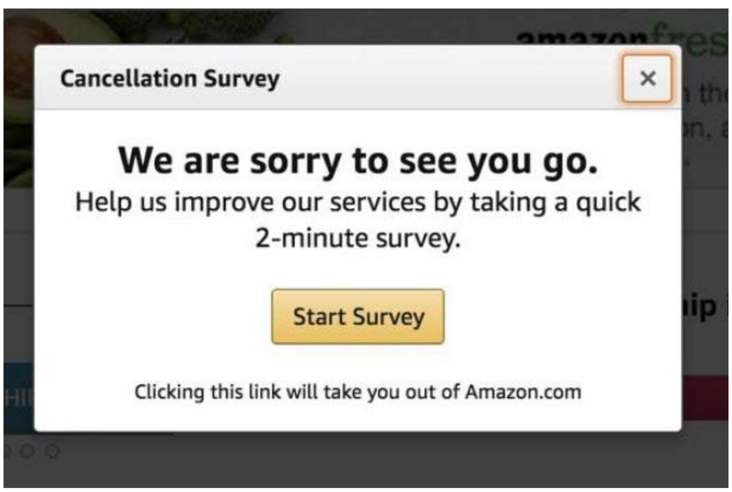
51 *See*, *e.g.*, AMZN_00021537 at 537; Kivetz Report, ¶ 25.

(51) A comment included in this internal Amazon document states "[T]he purpose of this project is to enable cancelation prediction using ML [Machine Learning] at scale."[52]

(52) Amazon used a few variations of the Survey until around April 2020.[53] Starting in early 2020, Amazon began to standardize the Survey method and questions.[54] Amazon invited, based on random selection, approximately [redacted]% of the customers who successfully cancelled their Prime subscription through the online cancellation process to complete the Cancellation Survey.[55] Since May 2020, Amazon has prompted [redacted] Prime customers who cancelled online to complete the Survey. Of these customers, about [redacted]% completed some or all of the Survey. Between May 2020 and June 2023, Amazon collected at least [redacted] Survey responses.

(53) Consumers who are selected for the Survey are shown the following pop-up window:

Figure 13: Screenshot of the Cancellation Survey pop-up window presented to randomly selected subscribers who cancelled online



Source: Kivetz Report, Figure 1.

(54) Consumers who click "Start Survey" are redirected to a platform outside of Amazon.com and presented a series of questions.[56] The first two questions (Q1 and Q2, reproduced below) ask respondents about their degree of satisfaction with Amazon and Prime, with five options presented in a fixed order from most to least satisfied.[57]

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52 *See*, *e.g.*, AMZN_00021537 at 537; Kivetz Report, ¶ 25.
53 Kivetz Report, ¶ 27.
54 *See*, *e.g.*, AMZN_00040674 at 677; Kivetz Report, ¶ 27.
55 *See*, *e.g.*, AMZN_00034290 at 291; Kivetz Report, ¶ 28.
56 *See*, e.g., AMZN_00001517–520; AMZN_00037417 at 425; Kivetz Report, footnote 43.
57 *See*, *e.g.*, AMZN-PRM-FTC-002704614 (emphasis in original); AMZN-PRM-FTC-002704651; Kivetz Report, ¶ 29.

Q1 Overall, how satisfied are you with **Amazon**?

- Very satisfied
- Somewhat satisfied
- Neither satisfied nor dissatisfied
- Somewhat dissatisfied
- Not satisfied at all

Q2 How satisfied are you with **Prime**?

- Very satisfied
- Somewhat satisfied
- Neither satisfied nor dissatisfied
- Somewhat dissatisfied
- Not satisfied at all

(55) Figure 14 summarizes Cancellation Survey responses for Questions 1 and 2 from the survey initiated in May 2020, with responses corresponding to subscriptions that ended on or before June 20, 2023.

Figure 14: Cancellation Survey responses for Question 1 and Question 2 (from the Survey initiated in May 2020, with responses from subscriptions that ended before June 21, 2023)

Response	Question 1 *Satisfaction with Amazon*	Question 2 *Satisfaction with Prime*
Very satisfied	[redacted]	
Somewhat satisfied		
Neither satisfied nor dissatisfied		
Somewhat dissatisfied		
Not satisfied at all		
Blank (i.e., no response recorded)		
Total responses		

Source: Survey response data (AMZN-PRM-FTC-DATA-00000017) for subscriptions cancelled on or before June 20, 2023.

(56) The next two questions (Q3 and Q4, reproduced below) ask respondents about their reason(s) for cancelling Prime.[58] The answer choices, except the "Other" option at the end, are presented in a randomized order.[59] For Q3, regarding their "main" reason for cancelling, respondents can only select

[58] *See, e.g.*, AMZN-PRM-FTC-002704619 (emphasis in original); AMZN-PRM-FTC-002704624; Kivetz Report, ¶¶ 30–31.

[59] *See, e.g.*, AMZN-PRM-FTC-002704653; AMZN-PRM-FTC-002704655; Kivetz Report, ¶¶ 30–31. Randomizing the order of responses (when responses do not have an intrinsically ordered meaning, such as least-to-most) is a standard and sound practice in survey design because it eliminates potential biases from anchoring behavior or consumer haste. *See, e.g.*, Shari Seidman Diamond, "Reference Guide on Survey Research," in *Reference Manual on Scientific Evidence: Third Edition*. (Washington, DC: The National Academies Press, 2011): 395–396 ("The order in which questions are

one answer. For each respondent, Amazon omits the response to Q3 from the list of responses to Q4.[60] Respondents can select multiple answers for Q4, unless they select "No, there were no other reasons" as their answer.[61]

Q3 What was your **main** reason for canceling Prime?

- The Prime membership fee was too expensive
- I was not making enough purchases on Amazon for it to be worthwhile
- I was not using the Prime benefits enough (e.g. Prime Video, Amazon Fresh, etc.)
- I experienced a problem with Prime (e.g. delivery issue, customer service problem, etc.)
- I did not intend to sign up for Prime
- Other (please specify) ____________

Q4 Are there additional reasons why you canceled your Prime membership? What are the other reasons? (select all that apply)

- No, there were no other reasons
- The Prime membership fee was too expensive
- I was not making enough purchases on Amazon for it to be worthwhile
- I was not using the Prime benefits enough (e.g. Prime Video, Amazon Fresh, etc.)
- I experienced a problem with Prime (e.g. delivery issue, customer service problem, etc.)
- I did not intend to sign up for Prime
- Other (please specify) ____________

(57) Additionally, later in the Survey, Amazon asks respondents who select "I experienced a problem" as their answer to Q3 or Q4 to identify the problem. Respondents can select multiple answers and the answer choices are not randomized.[62]

asked on a survey and the order in which response alternatives are provided in a closed-ended question can influence the answers…To control for order effects, the order of the questions and the order of the response choices in a survey should be rotated, so that, for example, one-third of the respondents have Product A listed first, one-third of the respondents have Product B listed first, and one-third of the respondents have product C listed first. If the three different orders are distributed randomly among respondents, no response alternative will have an inflated chance of being selected because of its position, and the average of the three will provide a reasonable estimate of response level.").

60 *See, e.g.*, AMZN-PRM-FTC-002704657; Kivetz Report, ¶ 31.

61 *See, e.g.*, AMZN-PRM-FTC-002704620; Kivetz Report, ¶ 31. The survey includes 11 questions in total. Kivetz Report, ¶¶ 29–37.

62 *See, e.g.*, AMZN-PRM-FTC-002704632; AMZN-PRM-FTC-002704669; Kivetz Report, ¶ 34 & footnote 55.

Q7 What problem(s) did you experience with Prime? (select all that apply)

- Deliveries were not made on time (after the date it was promised)
- I needed deliveries to arrive sooner than the promised date shown
- Deliveries were often stolen
- Order arrived broken
- Prime membership fee was charged to the wrong credit card
- Customer service was not able to resolve a problem with an order
- I did not intend to sign up for Prime
- Other (please specify) _____________

(58) Figure 15 summarizes Cancellation Survey responses for Questions 3 and 4 from the Survey initiated in May 2020.[63] This does not capture the full set of customers who did not intend to sign up for Prime because it does not include, e.g., customers who do not realize they have enrolled or who could not find the page needed to start the cancellation process. (I include tables displaying more detail on responses to Questions 3 and 4 and summary statistics for other Survey question responses in Appendix C.)

Figure 15: Cancellation Survey responses for Question 3 and Question 4 (from the Survey initiated in May 2020, with responses from subscriptions that ended before June 21, 2023)

Response	Question 3 *Main reason for cancelling*	Question 4 *Additional reasons*	Total
I experienced a problem with Prime (e.g. delivery issue, customer service problem, etc.)	[redacted]		
I did not intend to sign up for Prime			
The Prime membership fee was too expensive			
I was not using the Prime benefits enough (e.g. Prime Video, Amazon Fresh, etc.)			
I was not making enough purchases on Amazon for it to be worthwhile			
Other (please specify)			
No, there were no other reasons			
Blank (i.e., no response recorded)			
Total responses (including "Blank")			
Total responding subscribers			

Source: Survey response data (AMZN-PRM-FTC-DATA-00000017) for subscriptions cancelled before June 20, 2023.

[63] Excluding the "Blank" response, [redacted] subscribers responded to Q3 and 2.62 million responded to Q4, indicating that about [redacted] respondents both gave a non-blank answer to Q3 and left the Q4 response blank. Because Q4 allows for multiple responses while Q3 allows only one response, the total number of non-blank responses to Q4, at about [redacted], is higher than the total number of non-blank responses to Q3.

III.A.2. Academic economists and others commonly use surveys to make empirical inferences regarding populations of interest

(59) Surveys are commonly used by academic economists as a tool for analyzing consumer behavior and decision-making processes.[64] Surveys can provide information that is difficult to obtain through other methods, such as direct information about peoples' perceptions, knowledge, and beliefs.[65] In addition to academic settings, surveys are commonly used by businesses.[66] Surveys have also been used in legal settings to assess whether consumers are likely to have been misled by deceptive advertising.[67]

(60) Like any empirical data, survey evidence should be assessed for its reliability for answering the research questions at hand. Surveys can raise unique issues such as whether respondents are appropriately paying attention to the survey questions, and whether respondents tend to accurately recall past attitudes or behaviors.

(61) On the first issue, studies have found that provision of monetary incentives for completing a survey is not necessary and, indeed, may reduce attentiveness. For example, one recent study found that in a sample of survey respondents given monetary incentives to complete the survey, 7–9 percent failed an "attention check" item that was part of the survey.[68] But, in a survey sample where no monetary incentives were given, "hardly any of the respondents failed the attention checks."[69] The Amazon Cancellation Survey discussed here did not provide monetary incentives to participants.

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[64] For examples of peer-reviewed studies that use survey evidence, *see, e.g.*, Timothy G. Conley and Christopher R. Udry, "Learning about a New Technology: Pineapple in Ghana," *American Economic Review* 100, no. 1 (2010): 35–69, which uses a survey that asks respondents if they have ever received advice from a specific person. The authors use the answers to construct the network of advice giving and then trace how information disperses on the network. *See also* Alberto Alesina, Stefanie Stantcheva, and Edoardo Teso, "Intergenerational Mobility and Preferences for Redistribution," *American Economic Review* 108, no. 2 (2018): 521–554, which studies people's views on intergenerational mobility and redistribution and relies on survey responses regarding past behavior. *See, more generally,* John Bound, Charles Brown, and Nancy Mathiowetz, "Measurement Error in Survey Data," in *Handbook of Econometrics*, vol. 5: 3705–3843 at 3708 ("Empirical work in economics depends crucially on the use of survey data.").

[65] *See, e.g.,* Stefanie Stantcheva, "How to Run Surveys: A Guide to Creating your own Identifying Variation and Revealing the Invisible," *Annual Review of Economics* 15, no. 1 (2023): 205–234. *See also* Shari Seidman Diamond, "Reference Guide on Survey Research," in *Reference Manual on Scientific Evidence: Third Edition*. (Washington, DC: The National Academies Press, 2011, 361) ("Sample surveys are used to describe or enumerate the beliefs, attitudes or behavior of persons or other social units.").

[66] *See also,* Shari Seidman Diamond, "Reference Guide on Survey Research," in *Reference Manual on Scientific Evidence: Third Edition*. (Washington, DC: The National Academies Press, 2011): 364 ("Because the survey method provides an economical and systematic way to gather information and draw inferences about a large number of individuals or other units, surveys are used widely in business, government, and increasingly, administrative settings and judicial proceedings. Both federal and state courts have accepted survey evidence on a variety of issues.").

[67] Shari Seidman Diamond, "Reference Guide on Survey Research," in *Reference Manual on Scientific Evidence: Third Edition*. (Washington, DC: The National Academies Press, 2011): 361, citing Sanderson Farms v. Tyson Foods, 547 F. Supp. 2d 491 (D. Md. 2008).

[68] Hawal Shamon and Carl Clemens Berning, "Attention Check Items and Instructions in Online Surveys with Incentivized and Non-Incentivized Samples: Boon or Bane for Data Quality?" in *Survey Research Methods*, vol. 14, no. 1, 2020: 55–77.

[69] Hawal Shamon and Carl Clemens Berning, "Attention Check Items and Instructions in Online Surveys with Incentivized

(62) On the second issue, studies have found mixed results on the relationship between the length of the recall period and the quality of survey results, and some recent studies have found no relationship.[70] A summary of this literature found that "these more recent investigations point to the importance of the complexity of the behavioral experience over time, as opposed to simply the passage of time, as the factor most indicative of measurement error."[71]

(63) While survey data are not perfect, they can be useful, and particularly so when they provide information that is difficult to obtain through other methods. Confidence in survey results can be improved when they can be corroborated with other information available to the researcher on observed outcomes and behavior. For example, LaRue et al. (1979) compare the reliability of physicians' ratings and self-reported ratings and conclude that "self-reports of health were found to be significantly correlated with ratings assigned by a physician on the basis of medical records. […] The results suggest that self-reports could provide a valid, cost-effective means of health assessment in studies in which other forms of health information are lacking."[72] More recently, Hainmueller et al. (2015) compare results from a survey that asks participants about their attitudes towards the naturalization of immigrants with outcomes of voting on a referendum relevant to the same topic. The study finds that "the effects estimated from the surveys match the effects of the same attributes in the behavioral benchmark remarkably well."[73]

and Non-Incentivized Samples: Boon or Bane for Data Quality?" in *Survey Research Methods*, vol. 14, no. 1, 2020: 71 ("In Study 1, participants were gathered from a commercial access panel and monetary incentives were paid to respondents who completed the survey by the survey institute. In Study 2, participants were obtained from a noncommercial access panel, in which respondents were not promised any incentive for their participation…Results on the attention check items different substantially across the two samples. While in Study 1 (mixed motivation) about 7 percent (or 9 percent) of the respondents in Setting 2 and Setting 3 failed the first (or second) attention check item, in Study 2 (general intrinsic motivation), hardly any of the respondent failed the attention check items.").

70 John Bound, Charles Brown, and Nancy Mathiowetz, "Measurement Error in Survey Data," in *Handbook of Econometrics*, vol. 5: 3705–3843 at 3743–3744 ("Much of the measurement error literature has focused on the retrieval stage of the question answering process, classifying the lack of reporting of an event as a retrieval failure on the part of the respondent, comparing the characteristics of events which are reported to those which are not reported. One of the general tenets of this literature concerns the length of the recall period; the greater the length of the recall period, the greater the expected bias due to respondent retrieval and reporting error. This relationship has been supported by empirical data investigating the reporting of consumer expenditures and earnings [Neter and Waksberg (1964)]; the reporting of hospitalizations, visits of physicians, and health conditions [e.g., National Center for Health Statistics (1961, 1967), Cannell, Fisher and Baker (1965), Woolsey (1953)]; reports of motor vehicle accidents [Cash and Moss (1972)], crime [Murphy and Cowan (1976) and recreation [Gems, Ghosh and Hitlin (1982)]. However, even within these studies the findings with respect to the impact of the length of recall period on the quality of survey estimates vary. For example, Dodge (1970) found that length of recall was significant in the reporting of robberies but had no effect on the reporting of various other crimes, such as assaults, burglaries, and larcenies. Contrary to theoretically justified expectations, the literature also offers several examples in which the length of the recall period had no effect on the magnitude of response errors [see for example, Mathiowetz and Duncan (1988), Schaffer (1994)].").

71 John Bound, Charles Brown, and Nancy Mathiowetz, "Measurement Error in Survey Data," in *Handbook of Econometrics*, vol. 5: 3705–3843 at 3744.

72 Asenath LaRue, Lew Bank, Ussy Jarvik, and Monte Hetland, "Health in Old Age: How do Physicians' Ratings and Self-ratings Compare?," *Journal of Gerontology* 34, no. 5 (1979): 687–691.

73 Jens Hainmueller, Dominik Hangartner, and Teppei Yamamoto, "Validating vignette and conjoint survey experiments against real-world behavior," *Proceedings of the National Academy of Sciences* 112, no. 8 (2015): 2395–2400.

III.A.3. The Cancellation Survey is reliable and appropriate to use to evaluate unintentional enrollment in Prime

(64) At a high level, as I explained in Section III.A.1, Amazon's purpose for and design of the Cancellation Survey is consistent with its use by Amazon to evaluate consumer behavior and intent, particularly with respect to cancellation decisions. Amazon used the Survey to derive business-relevant information about customers who cancel, and I do the same.

(65) In this section, I explain why Amazon's Cancellation Survey provides a reliable basis from which to draw inferences regarding customer's unintentional enrollment in Prime.

III.A.3.a. The Cancellation Survey was appropriately designed

(66) Amazon invited, based on random selection, approximately [redacted]% of the customers who successfully cancelled their Prime subscriptions through the online cancellation process to complete the Cancellation Survey.[74] (See Section V.A.1.) The use of a survey fielded to a random sample of a population of interest and generating a sufficiently large number of respondents are standard components of a well-designed survey. In addition, as I show below, the observable characteristics of the responding and non-responding cancellers are similar.

(67) The Cancellation Survey questions were clear and non-leading, addressing concerns about demand effects.[75] The randomized order of the pre-populated answers (aside from "Other," which is always last) addresses potential bias from respondents more frequently selecting the responses at the top of the list. In addition, the questions did not encourage respondents to guess if they did not see their preferred response (for example, Questions 3 and 4 include an "Other" option). Additional—and substantive—validation comes from the fact, as I show later in this section, that Survey responses are related to consumer behavior in economically logical ways.

(68) Another potential issue in some survey contexts is that disaffected customers may be disproportionately likely to respond to a survey request. However, in this case, there is no a priori reason to expect that any disaffected customers who respond would be disproportionately likely to select "did not intend" over the other options that indicate dissatisfaction with Amazon. Moreover, the pop-up that invites randomly selected customers to participate in the Cancellation Survey states, "Help us improve our services …" (see Figure 13). This may have attracted customers who have disproportionately favorable views of Amazon. Ultimately, there are no theoretical or empirical reasons to think that the Survey respondents are non-representative in their likelihood to select "did

[74] *See, e.g.*, AMZN_00034290 at 291; Kivetz Report, ¶ 28.

[75] Dr. Kivetz characterizes "demand effects" as follows: "A fundamental survey principle is that a survey must avoid creating strong 'demand effects' (also referred to as 'demand characteristics'), whereby survey participants use cues provided by the survey's questions, answer choices, and/or stimuli to figure out the purpose of the study and the answers they think the researcher expects." Kivetz Report, ¶ 88.

not intend" on net. In fact, I find that survey respondents and non-respondents have similar characteristics, as I explain in the next section.

III.A.3.b. Survey respondents and non-respondents have similar observable characteristics

(69) One method to evaluate whether survey results are distorted by self-selection into the survey is to examine whether observable characteristics of survey respondents are similar to or distinct from those of customers who could have responded but did not. The logic is that, if the customers who choose to respond to the survey are fundamentally different types of customers than those who do not respond, then their characteristics should also be significantly different.

(70) Figure 16 compares the distributions of Prime subscription lengths between two groups in the [redacted] sample: Survey respondents, and subscribers who cancelled subscriptions and were offered the Survey but did not respond. Figure 17 shows the distributions of shipping benefit use for these two samples. I focus on these two characteristics because the regression model I use to estimate the rate of unintentional enrollment in the broader Prime population indicates that these two factors are important predictors. (*See* Appendix D.3, Figure 52 and Figure 54). The figures demonstrate that Survey respondents and non-respondents have similar observable characteristics. Given that customers in the two groups do not exhibit large differences, there is no basis to expect their Survey responses would have large differences. Still, in the regression analysis that underpins the harm calculations, I control for observable characteristics, including these two measures.

Figure 16: Distribution of Prime subscription lengths

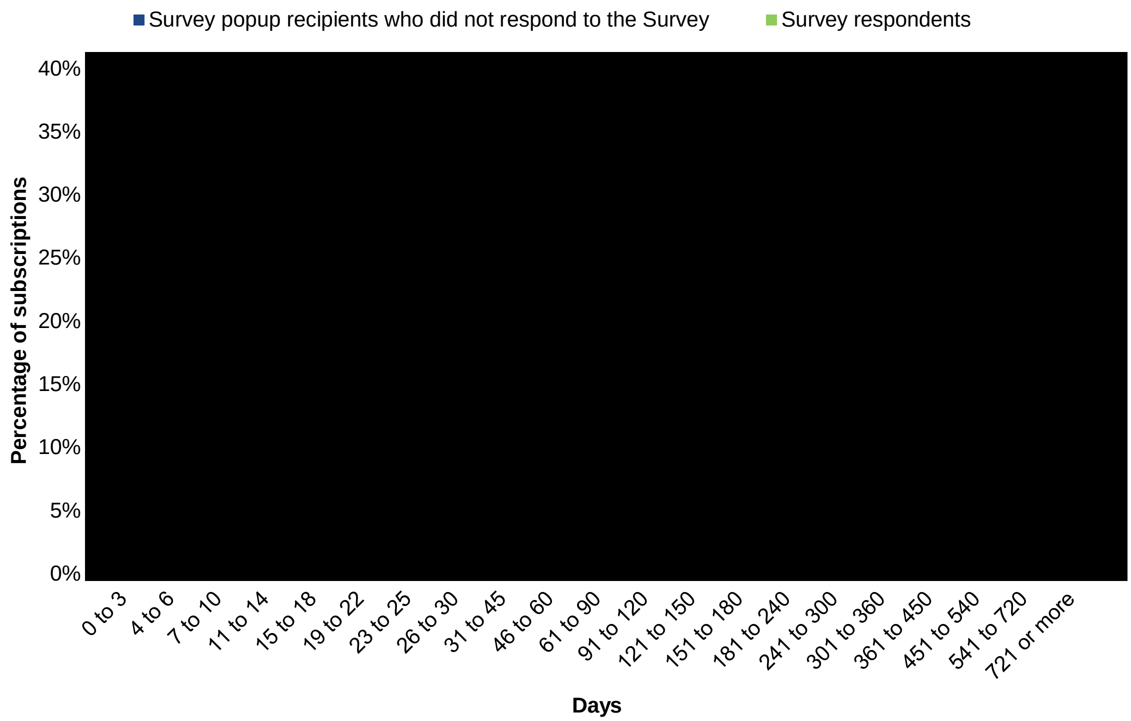
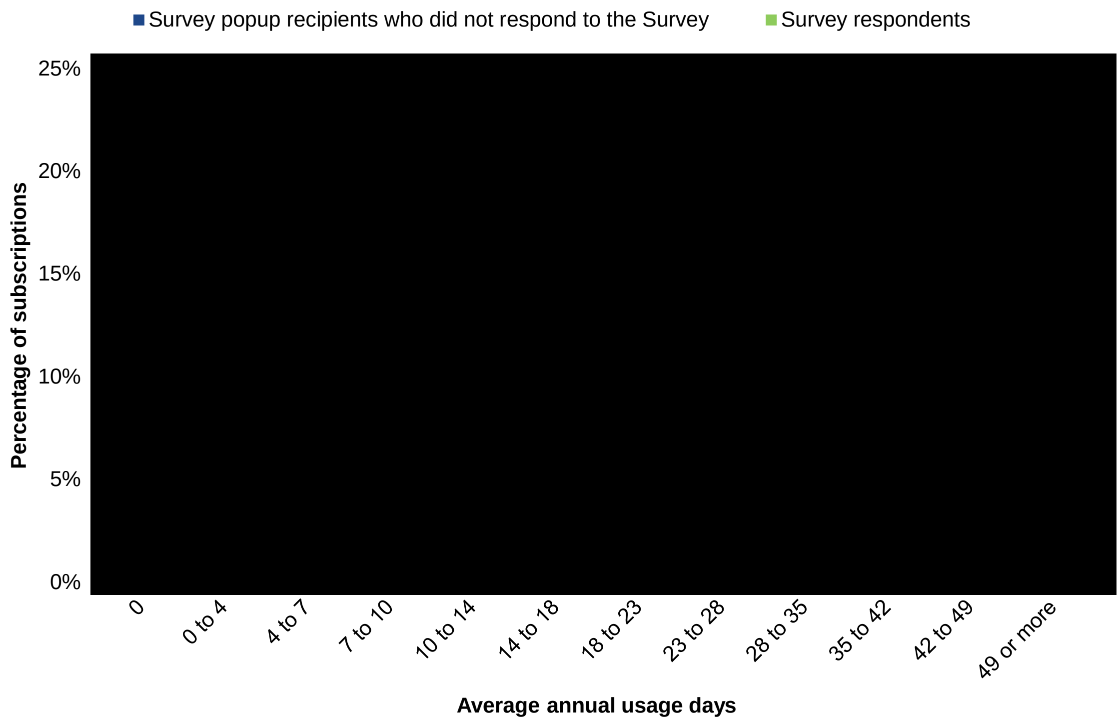


Figure 17: Distribution of Prime shipping benefit use



III.A.3.c. Survey responses show that many subscribers were unintentionally enrolled in Prime

(71) As described above, the Cancellation Survey asks various questions about customers' experiences with Prime. The first two ask about the customer's satisfaction with Amazon and Prime. As seen in Figure 18, the first two questions show "Very satisfied" as the first response and "Not satisfied at all" as the last response. The third question asks for the customer's "**<u>main</u>** reason" for cancelling Prime, and the fourth question asks for any "additional reasons" the customer cancelled Prime.

(72) As seen in Figure 18, approximately [redacted] of Survey respondents said they were somewhat satisfied or very satisfied with Amazon and approximately [redacted]% said they were somewhat satisfied or very satisfied with Prime. The remaining respondents were either neutral or expressed dissatisfaction [redacted]% of respondents did not indicate their degree of satisfaction with Prime). Approximately [redacted]% of Survey respondents said they were somewhat dissatisfied or not satisfied at all with Amazon and approximately [redacted]% said they were somewhat dissatisfied or not satisfied at all with Prime.

Figure 18: Cancellation Survey responses about satisfaction with Amazon and Prime

Response	Satisfaction with Amazon (percent of responses)	Satisfaction with Prime (percent of responses)
Very satisfied	[redacted]	
Somewhat satisfied		
... "Satisfied" Subtotal		
Neither satisfied nor dissatisfied		
Somewhat dissatisfied		
Not satisfied at all		
... "Dissatisfied" Subtotal		
Blank		

(73) Figure 19 uses the information from the third and fourth questions of the Survey to compare satisfaction responses to the first two questions. I consider individuals as unintentional enrollees if they responded that they did not intend to sign up to either the third or fourth question. Overall satisfaction with Amazon and Prime was generally lower for unintentional enrollees than for customers who did not indicate they signed up unintentionally. In particular, [redacted] of unintentional enrollees responded that they were "Not satisfied at all" with Prime compared to [redacted]% of other respondents.

Figure 19: Cancellation Survey satisfaction responses for respondents who said they did not intend to sign up for Prime

	Satisfaction with Amazon: Percent of responses		Satisfaction with Prime: Percent of responses	
Response	Others	Unintentional enrollees	Others	Unintentional enrollees
Very satisfied	[redacted]			
Somewhat satisfied				
Neither satisfied nor dissatisfied				
Somewhat dissatisfied				
Not satisfied at all				
Blank				

Note: Data limited to subscribers who responded to Q3 or Q4.

(74) Figure 20 summarizes the shares of responses that indicate satisfaction, dissatisfaction, or neither with Amazon for each response to the third question regarding the main reason for cancelling Prime. Figure 21 shows the shares of responses that indicate satisfaction, dissatisfaction, or neither with

Prime for each response to the third question. The most dissatisfied category of respondents was those who indicated they experienced a problem with Prime; these were followed by respondents who indicated they did not intend to sign up for Prime and those who indicated some other reason for cancellation. Regarding satisfaction with Amazon, [redacted] of respondents who experienced a problem were dissatisfied, compared to [redacted]% of respondents who did not intend to sign up. The pattern is similar for satisfaction with Prime, with [redacted] of respondents who experienced a problem being dissatisfied, compared to [redacted]% of respondents who did not intend to sign up.

Figure 20: Cancellation Survey Question 1 (satisfaction with Amazon) responses, by reason for cancelling Prime (Question 3)

Reason for cancelling Prime	Satisfied	Neither satisfied nor dissatisfied	Dissatisfied
I experienced a problem with Prime (e.g. delivery issue, customer service problem, etc.)	[redacted]		
Other (please specify)			
I did not intend to sign up for Prime			
Blank (i.e., no response recorded)			
The Prime membership fee was too expensive			
I was not using the Prime benefits enough (e.g. Prime Video, Amazon Fresh, etc.)			
I was not making enough purchases on Amazon for it to be worthwhile			

Figure 21: Cancellation Survey Question 2 (satisfaction with Prime) responses, by reason for cancelling Prime (Question 3)

Reason for cancelling Prime	Satisfied	Neither satisfied nor dissatisfied	Dissatisfied	Blank
I experienced a problem with Prime (e.g. delivery issue, customer service problem, etc.)	[redacted]			
I did not intend to sign up for Prime				
Other (please specify)				
Blank (i.e., no response recorded)				
The Prime membership fee was too expensive				
I was not using the Prime benefits enough (e.g. Prime Video, Amazon Fresh, etc.)				
I was not making enough purchases on Amazon for it to be worthwhile				

(75) As is true with any survey, some customers who fill out the Cancellation Survey may not respond entirely accurately, either intentionally or by accident. However, there is no reason to expect that any such inaccurate responses would meaningfully or systematically impact the percentages reported in the above figures.

(76) One could imagine a customer who was unhappy with their Prime experience and decided to cancel, and therefore tried to respond in a way that could grant them a refund. Insofar as there are any such customers, selecting "I did not intend to sign up for Prime" is not a more logical choice than other responses such as experiencing a problem with Prime.

(77) A customer may also not respond accurately if they select responses at random or tend to pick, e.g., the first response to every question. In both cases, the behavior would not result in disproportionate selection of "I did not intend to sign up for Prime." Amazon presents the responses in random order (with the exception of "Other (please specify)," which is always last)[76] so "I did not intend to sign up for Prime" does not appear as the first response to Question 3 or Question 4 any more frequently than the other listed responses.

(78) One could imagine customers who do not find an option that accurately reflects the reason they cancelled Prime simply clicking "I did not intend to sign up for Prime" in order to advance through the questions. For these customers, however, Amazon provides alternative responses: the "Other" response to Question 3 and the "Other" and "No, there were no other reasons" responses to Question 4.

(79) Lastly, one might expect customers who are disproportionately dissatisfied with Prime to skew their responses in a particular way. While respondents who indicated they did not intend to sign up were generally less satisfied than all other respondents, they are not the least satisfied respondents. Figure 20 and Figure 21 above show that customers who reported experiencing a problem with Prime were the least satisfied with both Amazon and Prime.

III.A.3.d. Prior cancellation surveys also show that many customers were unintentionally enrolled in Prime

(80) Amazon also conducted cancellation surveys prior to May 2020 that offered respondents an option to indicate that they unintentionally subscribed to Prime.[77] Figure 22 shows the results of these earlier surveys. Compared with the Cancellation Survey that I use for my analyses, these surveys show an overall higher rate of responses indicating unintentional enrollment. In particular, for the prior surveys with the most similarly worded option to indicate unintentional enrollment ("I did not *mean* to sign up for Amazon Prime" rather than "I did not *intend* to sign up for Prime"), the shares of customers who indicated unintentional enrollment are uniformly larger than in the Cancellation Survey (which shows a "did not intend" response rate of [redacted]%). This implies that it is reasonable if not conservative to use data from the Cancellation Survey to estimate rates of unintentional enrollment prior to May 2020.

[76] Kivetz Report, ¶ 30; AMZN-PRM-FTC-002704653

[77] Kivetz Report, ¶ 27.

Figure 22: Results from cancellation surveys prior to May 2020

Survey No.	Wording	Dates	Responses	Share
1	I did not mean to sign up for Amazon Prime	03/27/2020–05/04/2020	[redacted]	
2	I did not remember I signed up for Prime until I got charged	11/07/2018–03/02/2019		
3	Experienced a sign-up or cancellation problem with Amazon Prime	09/17/2018–03/31/2020		
4	I did not mean to sign up for Amazon Prime	11/07/2018–02/17/2019		
5	I did not mean to sign up for Amazon Prime	11/06/2018–03/05/2019		
6	I did not mean to sign up for Amazon Prime	11/06/2018–03/01/2020		
7	I did not mean to sign up for Amazon Prime	11/06/2018–04/26/2019		
8	I did not mean to sign up for Amazon Prime	04/03/2020–05/06/2020		
9	I did not mean to sign up for Amazon Prime	11/06/2018–04/02/2019		

III.A.4. Rates of "did not intend" Cancellation Survey responses over time support the conclusion that the Survey accurately captures the rate of unintended signups

(81) The FTC has represented to me that Amazon changed its UPDP upsell at various points in time. They have asked me to quantify, for subscribers who joined via UPDP ("UPDP subscribers"), the frequency at which Cancellation Survey respondents indicate that they did not intend to sign up for Prime, separately for subscribers who joined Prime via UPDP in five distinct time periods. The time periods correspond to different formats of the UPDP upsell.

(82) In general, during periods in which Amazon implemented clarity or user experience ("UX") improvements in the UPDP upsell, the Cancellation Survey generates fewer "did not intend" responses. This has two implications. First, it provides support for the reliability of the Survey with respect to unintentional enrollment rates. Second, it provides evidence that less clarity on the Amazon UPDP upsell results in higher rates of unintentional enrollments.

(83) **Time Period 1: UPDP subscribers as of March 19, 2020 and prior.** The FTC has represented that on or around March 20, 2020, in response to shipping issues caused by the onset of the COVID-19 pandemic, Amazon stopped offering "free trial" Prime upsells, such as UPDP, during product checkout.[78] The Cancellation Survey data on which I rely began in 2020, so data are sparse for this period.

(84) **Time Period 2: April 23, 2020 through September 16, 2020.** The FTC has represented to me that on or around April 22, 2020, Amazon resumed "free trial" Prime upsells during product checkout.[79]

[78] AMZN_00107862.

[79] AMZN_00107862.

The FTC has further represented that, through on or about September 17, 2020, UPDP upsells did not make shipping-time representations or include signup buttons such as "Get Free Two-Day Shipping," which the FTC has alleged to be unclear.

(85) **Time Period 3: September 17, 2020 through December 2, 2020.** The FTC has represented to me that on or around September 17, 2020, Amazon changed the UPDP upsell in two main ways: (1) reverting to pre-COVID shipping-based upsells (e.g., "Get Free Two-Day Shipping" to shoppers who were buying a Prime-shipping-eligible item) and (2) making certain changes that Amazon predicted would improve the "clarity" of the UPDP enrollment page, as compared to the pre-COVID version of UPDP.[80] The FTC has further represented that, on or around December 3, 2020, Amazon reverted its UPDP upsell to the pre-COVID version.[81]

(86) **Time Period 4: December 3, 2020 through January 31, 2022**. This period starts with the date on which the FTC has represented that Amazon returned the UPDP upsell page to the pre-COVID format. The FTC has also represented that Amazon did not make further significant UPDP changes until it implemented what Amazon refers to as "CX Satisfaction Changes" between February 1 and February 9, 2022.[82]

(87) **Time Period 5: February 10, 2022 through the end of the my data set (June 21, 2023).** The FTC has represented that Amazon did not make significant changes to UPDP after February 9, 2022 and, thus, the "CX Satisfaction Changes" were in effect during this period.

(88) Figure 23 shows the rates at which UPDP subscribers indicated on the Cancellation Survey that they did not intend to enroll in Prime during the five time periods. The rates of "did not intend" responses are [redacted] during (1) the time period in which the FTC indicates that Amazon was not offering free two-day shipping upsells (time period 2) and (2) the time periods in which the FTC indicates that Amazon implemented clarity improvements (time periods 3 and 5). For these periods, the rate of "did not intend" responses is between [redacted]% and [redacted]%. In contrast, for UPDP signups during the 14-month duration of time period 4—when Amazon returned to the pre-COVID UPDP format that includes shipping-based upsells but not clarity or CX Satisfaction improvements—the rate of "did not intend" responses is [redacted]%.[83]

(89) The pattern is consistent with the premise that Amazon's clarity improvements explain the reductions in the rates of "did not intend" responses. This implies that the absence of those clarity improvements

80 AMZN_00107862; AMZN_00102785 at 785–789.

81 AMZN_00107862 at -863; AMZN_00016867 at -868.
The FTC has also represented to me that a sample UPDP from Time Period 1 (before COVID) is pictured at AMZN_00102785 at -789 and a sample UPDP from Time Period 3 is pictured at AMZN_00102785 at -788.

82 AMZN-PRM-FTC-002670757-758; AMZN-PRM-FTC-001327233.

83 The differences between the [redacted] rates of "did not intend" responses during periods in which the FTC indicates that Amazon implemented clarity improvements and the rates in other periods are statistically significant at the [redacted]% level.

results in [redacted] rates of unintentional enrollments. (It also appears that the pause in shipping-based upsells resulted in [redacted] unintentional enrollments.)

Figure 23: "Did not intend" responses among UPDP enrollees, by time period of enrollment

Time Period of UPDP enrollment		"Did not intend" responses	
		Count	Percent
Time Period 1 (sparse Survey data)	March 19, 2020 and prior	[redacted]	
Time Period 2 (no shipping-based upsells)	April 23, 2020–September 16, 2020		
Time Period 3 (2020 clarity improvement)	September 17, 2020–December 2, 2020		
Time Period 4 (return to pre-COVID)	December 3, 2020–January 31, 2022		
Time Period 5 (CX Satisfaction Changes)	February 10, 2022–June 20, 2023		

III.A.5. Data on Prime benefit usage and the Cancellation Survey data are consistent

(90) As discussed in Section II.E, it is a common practice in economics to validate survey results using available non-survey data on consumer attributes and behavior. In this case, Amazon data on enrollee usage of Prime benefits allow me to test, and ultimately corroborate, the Survey results by comparing Prime benefit usage for those who reported unintentionally signing up for Prime. To the extent the Survey is correctly reporting unintended enrollments, usage of Prime benefits should be lower for those who report unintentionally enrolling than for those who do not.

(91) Prime subscribers pay fees for the service and can get access to benefits such as free shipping on purchases and additional video and music streaming services. Prime shipping is a particularly useful form of Prime usage data. When Prime subscribers make purchases on Amazon's e-commerce platform, their shipping option defaults to free shipping available to Prime subscribers.[84] So a comparison of Prime shipping usage between those who report unintentionally signing up for Prime and those who give other responses can help evaluate the results of the Survey. Other Prime benefits, such as streaming services, require Prime subscribers to go to a dedicated app or Amazon webpage for access, which may make such benefits a less useful signal.

[84] Amazon's Supplemental Objections & Responses to FTC's Third Set of Interrogatories (March 21, 2025), pp. 11–16.

(92) Figure 24 shows a clear pattern of [redacted] Prime shipping usage among customers who indicated they did not intend to sign up. This is consistent with the idea that someone who is not aware of their Prime membership would use fewer benefits, thus corroborating the Survey results.[85]

Figure 24: Prime shipping benefit use normalized by subscription length for unintentional enrollees and others, by signup method

III.B. Estimating harm from Amazon's unintentional enrollments in Prime

(93) Given that the Cancellation Survey was offered to and completed by a subset of consumers who may have been harmed by Amazon's conduct, I extrapolate from the Survey results to reasonably and reliably estimate the harmed population of unintentional Prime subscriptions and the resulting additional subscription fees paid by customers.

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[85] To reiterate, this sample includes only customers who cancelled their Prime memberships; accordingly, this shows that before cancelling, customers who indicated that they never intended to sign up for Prime had lower usage than customers who provided a different explanation for cancelling. In addition, customers can have positive usage even if they do not realize that they are enrolled in Prime; for example, shipping benefits generally select to Prime by default.

(94) Using the Survey to estimate the number of unintentional enrollees is conservative for two reasons. First, Amazon only offers the Survey to Prime subscribers who eventually realize they are Prime subscribers and complete Amazon's online Iliad cancellation process. The Survey results do not include unintentional enrollees who did not become aware of their Prime status during the analysis period or who cancelled by contacting customer service. Second, as shown in Section III.A.3.d, prior cancellation surveys with comparable wording to indicate unintentional enrollment indicate higher rates of unintentional enrollment.[86] However, these prior cancellation surveys cannot be linked to the customer data produced by Amazon.[87] Accordingly, to measure harm in the period before May 2020 period, I apply unintentional enrollment rates derived from the Cancellation Survey (which can be linked to the Amazon customer data); this is likely to be conservative in the direction of under-identifying customers harmed by unintentional enrollments.

(95) To estimate the rate of harmed subscriptions, I use a prediction model based on a linear regression. This regression model uses the population of Survey respondents to estimate a statistical relationship between (1) an indicator for whether a Survey respondent indicated they did not intend to sign up (the outcome of interest) and (2) relevant characteristics of the consumer's subscription (the variables).[88] I use this model to predict the unintentional signup rate among Prime subscribers who cancelled their account. Finally, I calculate the expected value of the corresponding additional payments by customers from these unintentional enrollments.[89]

(96) The characteristics I use in the regression model are informed by my analysis of the Amazon customer data and Cancellation Survey data as well as the institutional environment (e.g., Amazon's signup methods, the Iliad cancellation process, etc.). The variables that I include are ones that could be associated with likelihood that an Amazon customer inadvertently and unintentionally became a Prime member. Because my goal is to derive a prediction of the probability of an unintentional signup

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86 In a cancellation survey conducted by Amazon from November 1, 2019–February 28, 2019, [redacted]% of US respondents indicated their reason for cancellation was "I did not mean to sign up for Amazon Prime." AMZN_00003642 at 643.

87 *See* Section II.D.

88 Joshua D. Angrist and Jörn-Steffen Pischke, "Mostly Harmless Econometrics: An Empiricists Companion," (Princeton, NJ: Princeton University Press, 2009).

89 In this report, I only calculate harm due to the at-issue "upsell" signup methods (SOSP, SPC, and UPDP). There are likely additional unintentional enrollments through other signup methods, for instance when someone signs up for a trial subscription on the Amazon web page and the trial subscription becomes a paid subscription because auto-renew was unintentionally turned on.

for consumers with varying characteristics (rather than to estimate the marginal effects of specific individual customer characteristics), I include a broad set of variables:[90, 91]

- signup method (UPDP, SOSP, SPC)
- Prime and non-Prime benefit use across nine possible categories of benefits
- length of a subscription
- calendar quarter of signup
- device on which a consumer signed up
- signup number for consumers who signed up for Prime multiple times
- whether a subscription ever benefitted from discounted student rates
- whether the consumer turned off the auto-renew feature of Prime
- whether the subscription began with a trial plan
- whether there was ever a billing problem at some point during the subscription

(97) Because, as shown above, Prime benefits usage and rates of unintentional enrollment vary across signup methods, I fully interact the signup method with all other regressors.[92]

(98) In estimating the rate of unintentional Prime subscriptions, I limit to subscriptions that (1) began on or after January 1, 2018, (2) were (as with the Cancellation Survey respondents' subscriptions) cancelled before June 21, 2023, (3) consisted wholly or partly of monthly plans, and (4) were initiated via the UPDP, SOSP, and SPC signup methods.[93] In estimating excess payments for unintentionally enrolled Prime subscriptions, I further limit to (1) payments for monthly plans, (2) payments that

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[90] Gareth, James, et al., eds. "Statistical Learning." *An Introduction to Statistical Learning*, 2nd ed. (New York: Springer Science+Business Media, 2013) at 24–25 and 243–244 discuss modeling practices when the goal is predictive accuracy rather than inference. As they explain, including many variables can lead to collinearity but that does not reduce the predictive accuracy of a model. *See also*, Peter E. Kennedy, "A Guide to Econometrics," 4th ed. (Massachusetts: The MIT Press, 1998) at 184 (explaining that the OLS estimator remains unbiased in the presence of multicollinearity).

[91] In addition, internal Amazon emails identify the types of variables I include as being predictive of unintentional enrollment. *See, e.g.*, AMZN_00041335.

[92] This design allows the regression to capture the relationship between unintentional enrollments and any interacted regressor (in this example, subscription length), independently for each signup method. For example, the included regressors that relate to *subscription length* are *subscription length; subscription length* × *1[signup = SOSP];* and *subscription length* × *1[signup = SPC]*. The function, 1[], is the indicator function, which equals 1 if the statement inside the brackets is true. The "omitted category" is UPDP (i.e., I do not include interaction terms based on *1[signup = UPDP],* because the effect of the signup method being UPDP is captured by the indicators for the other signup methods equaling zero).

[93] I limit to subscriptions that began on or after January 1, 2018, because the cancellation data produced by Amazon do not identify cancellations and other subscription terminations prior to this date. Further, I limit to subscriptions that were cancelled prior to June 21, 2023, because the Amazon benefit usage data do not extend beyond this date. In addition, I limit to subscriptions that include monthly plans because that is the plan type that unintentional enrollees are subscribed to by default.

were made on or before a subscriber first entered a cancellation process (even if they did not successfully cancel), and (3) payments made on or after a cutoff date of December 29, 2018.[94]

(99) To estimate the regression model, I use the randomly selected "[redacted] sample (*see* Section II.D). This sample includes [redacted] out of [redacted] subscriptions that began after January 1, 2018. In the final step I multiply the damages estimate from the [redacted] sample by [redacted] ÷ [redacted] = [redacted] in order to calculate the corresponding value for the population of unintentional Prime enrollees.

(100) As shown in Figure 25, across the upsell signup methods, I estimate [redacted] unintended subscriptions and $844 million in harm, where I calculate harm as total payments made between the subscription start date and the date of first cancellation process entry for unintended subscriptions.

Figure 25: Harm estimate for customers' unintentionally enrolled subscriptions via upsell signups

Signup method	Share of unintentional enrollments	Count of unintentional enrollments ($M)	Harm from unintentional enrollments ($M)[95]
SOSP	[redacted]		[redacted]
SPC			
UPDP			
TOTAL			**$844**

(101) Appendix D.3 includes charts showing how the predicted proportion of harmed subscriptions varies with (1) the average usage of Prime shipping benefits during a year, (2) the average usage of non-shipping Prime benefits during a year, and (3) the length of a subscription.[96] These show that the regressors included in my model are predictive of the rate of unintentional enrollment. The predicted rate of harmed subscriptions for all three signup methods at issue is higher for shorter subscriptions, as well as for subscriptions with lower usage of Prime shipping benefits and non-shipping Prime benefits.

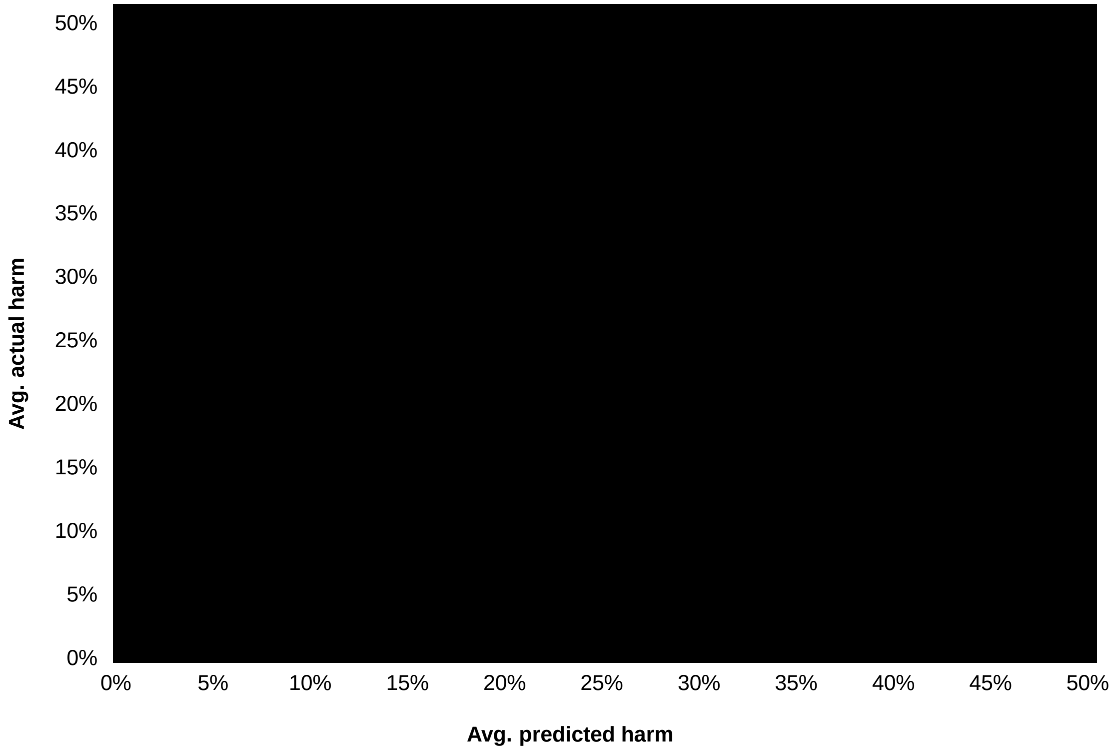
(102) Additionally, to assess the reliability of the model at predicting average rates of harmed subscriptions, I compare the predicted share of unintentional enrollments among Survey respondents (computed without accounting for their actual Survey responses) against the actual share of unintentional enrollments among Survey respondents. As Figure 26 shows, actual and predicted shares are closely related, which confirms the reliability of my model.

[94] Estimates of excess payments from unintentional enrollment after other date cutoffs are in Appendix D.4.

[95] These harm estimates, and all other harm estimates in this report are rounded *down* to the nearest million.

[96] *See* Appendix D.3.

Figure 26: Comparison of average predicted harm against average actual harm



[redacted]

(103) As a sensitivity check, in Appendix D, I present two other versions of my baseline model for estimating the number of unintentional enrollments and the related estimates of harm from additional Prime monthly payments.

- First, I estimate my baseline model only on subscriptions that ended after the Cancellation Survey began (May 2020), so as to overlap fully with the period in which the Cancellation Survey was conducted. The resulting estimates of the rate of harmed subscriptions across signup methods are [redacted]% of applicable Prime subscriptions, which is similar to the [redacted]% range seen in Figure 25.
- Second, I estimate my baseline model using a logistic regression instead of a linear regression. This is an alternative regression specification that can be used to predict outcomes that are categorical, such as unintentional enrollment versus other enrollment.[97] The resulting estimates of the rate of harmed subscriptions across signup methods for the same subscriptions as my linear regression baseline are [redacted]%, which is also close to the corresponding range in Figure 25.

[97] Joshua D. Angrist and Jörn-Steffen Pischke, *Mostly Harmless Econometrics: An Empiricists Companion* (Princeton, NJ: Princeton University Press, 2009).

(104) Additionally, in Appendix D, I present two alternative methodologies for estimating the number of unintentional enrollments.

- The first (Alternative method 1) is a more straightforward approach to estimating the total number of unintended subscriptions by applying the proportion of unintended subscriptions in the Cancellation Survey population to the population of Prime subscriptions, subject to the same exclusions as my baseline method, separately for each signup method. This approach assumes that Survey respondents are similar to and reflective of the total population of Prime subscribers for each enrollment channel.
- The second (Alternative method 2) is a more flexible version of this approach that matches subscriptions among Survey respondents who identify as unintentional enrollees to the broader population of Prime subscriptions at a more granular level. By matching like behaviors (e.g., subscription characteristics) between those two groups, one can then make reasonable estimates of other traits, such as "did not intend" rates.

(105) Applied to the same set of subscriptions, Alternative method 1 yields a higher estimate of harm from additional monthly payments for Prime than my baseline method of $939 million and Alternative method 2 yields a similar estimate to my baseline of $842 million. For each of my three methods, I also include analogous estimates for various alterative cutoff dates in the same appendix.

(106) Finally, I also include in Appendix D an extrapolation from my baseline method that extends the estimation of harm to cover the period from June 21, 2023, to September 30, 2025. To extrapolate, I estimate the predicted harm by month of subscription cancellation for the last 12 consecutive full months included in my baseline method (June 2022–May 2023). I then average this estimate to obtain an average predicted harm per month and calculate total harm over the extended period from June 21, 2023, to September 30, 2025, assuming harm accrues at the same rate. Across signup methods, the estimated harm during this post-June 21, 2023 period is $475 million.

IV. Harm to consumers who are unsuccessful at cancelling Amazon Prime

(107) Many Prime subscribers who try to cancel their subscriptions online do not complete Amazon's Iliad cancellation process.[98] While some of these incomplete cancellations may be intentional, others may reflect subscribers who either believed that they successfully cancelled when in fact they did not or who gave up trying to cancel despite still having the intent to cancel. The first category, intentional incomplete cancellations, would include, for instance, subscribers who start the cancellation process but are persuaded by an offer that Amazon presents to them. These subscribers would exit the Iliad process with the knowledge that they did not cancel their Prime subscription.

(108) The second category, unsuccessful cancellers, would include, for instance, Prime subscribers who are diverted away from the Iliad process when they click on one of several buttons or links in the Iliad process, and subscribers who close their browsers or navigate to other websites. Some of these subscribers may believe, incorrectly, that they successfully cancelled. Others may be subscribers who maintain an intent to cancel but were unable to successfully complete the Iliad process.

(109) Regardless of subscribers' intent and beliefs when they exit the Iliad process, Amazon continues to charge those subscribers the Prime fee until they successfully cancel their subscriptions. To the extent that the design of the Iliad process misleads or confuses subscribers into falsely believing that they cancelled their subscription, those subscribers would be paying for Prime benefits that they think they no longer have. In this section, I provide my methodology and estimates of the number of such harmed subscribers and the additional amounts they paid in Prime fees as a result.

(110) My estimates are conservative in several respects. First, I do not include Prime subscribers who would like to cancel but cannot find the End Membership option to initiate the Iliad cancellation process.[99] Second, I do not include subscribers who are knowingly deterred or diverted from cancelling due to difficulty navigating the Iliad cancellation process. Third, I do not include economic harm from unsuccessful cancellations by subscribers who tried but failed to cancel through other means (e.g., by phone).

(111) In addition, my current analysis does not include harm to subscribers who were unsuccessful at cancelling through the Iliad 2.0 process described in Section II.C. Amazon's data only provide several months of information about subscribers who used Iliad 2.0 after it was launched, from around April

[98] When defining Prime subscribers who "cancel" their membership, I also include subscribers who turn off auto-renew or pause their membership. As noted above in Section II.C and seen in Figure 10, customers can pause their membership through the Iliad process, which I treat as a cancellation.

[99] As noted above in Section II.C, it generally takes multiple steps for a customer to reach the End Membership option (e.g., select "Accounts & Lists" to get a dropdown menu, then click on "Prime Membership," then click on "Manage Membership," then click on "End Membership").

2023 through June 2023. To the extent Amazon produces additional data covering the period since June 2023, as the FTC has requested, I reserve the right to analyze such data for harm from unsuccessful cancellations and to supplement my estimates.

IV.A. Many Prime subscribers exit Amazon's online cancellation process without successfully cancelling

(112) Between July 2019 and March 2023, Prime subscribers entered Amazon's "Iliad" cancellation process approximately [redacted] times. Of those entries, approximately [redacted] did not result in a completed cancellation. Among the subscribers who entered the Iliad process but did not cancel during their first entry, [redacted]% percent continued to pay Prime subscription fees to Amazon after their first entry into the Iliad process (the remainder cancelled at some point after the date of entry but before the next payment date).[100]

(113) As described in Section II.C, a Prime subscriber can take several actions during the cancellation process that result in exiting the Iliad process. On the one hand, if a Prime subscriber reaches the final page of the Iliad process and selects the option to cancel their subscription, the result is a successful cancellation. Any other action leads to an incomplete cancellation, whether intentional or not. Based on my analysis of Amazon's data covering subscribers who reached the three-page portion of the Iliad process between July 2019 and March 2023, and the subsequent actions such subscribers took, I group actions that result in incomplete cancellations into the following categories:

- "Accept an Offer"—Clicking on a button on the Offer Page to accept an offer presented by Amazon as an incentive to continue as a Prime subscriber.
- "Keep My Benefits/Keep My Membership"—Clicking on the Keep My Benefits button on the Marketing Page, or the Keep My Membership button on either the Offer Page or the Cancellation Page.
- "Remind Me Later"—Clicking on the Remind Me Later button on the Marketing, Offer, or Cancellation pages.
- "No Page"—Navigating away from the Iliad process, e.g., by going to a non-Amazon website or closing the browser, or taking no action on any page of the Iliad process for at least 2 hours.[101]

[100] *See* Figure 32 and Appendix E.3 for details on the composition of users who enter the Iliad cancellation process, some of whom I conclude were harmed through unsuccessful cancellations.

[101] I categorize a subscriber's action as "No Page" if the last action that subscriber took in the Iliad process did not lead to a successful cancellation and no further action was recorded in the data.

- "Prime Central"—Clicking on a link or feature in the Iliad process that returns the subscriber to the Prime Central Page (other than clicking on the Keep My Benefits/Keep My Membership or Remind Me Later buttons).
- "Other"—Taking any other action that leads to exiting the Iliad process without completing cancellation.

(114) Figure 27 illustrates the count and share of subscriptions by action group for Iliad entries.

Figure 27: Actions by subscribers who enter the Iliad process but do not pause or cancel

Action	Count of subscriptions (thousands)	Share of subscriptions
Accept an Offer	[redacted]	
No Page		
Prime Central		
Remind me Later		
Keep My Benefits/Keep My Membership		
Other		

IV.B. Subscribers who do not successfully cancel use fewer Prime benefits on average

(115) One lesson from the behavioral economics literature, which I discussed in Section II.E, is that a proliferation of options, as well as the "choice architecture" of how those options are presented, can cause consumers to make choices that do not reflect their underlying intentions. In the present context, this implies that some subscribers who took an action other than "Accept an Offer" in the Iliad process may have exited with the belief that they successfully cancelled their Prime subscription when in fact they did not.

(116) For example, subscribers may click on the Continue To Cancel button twice in the Iliad process—once on the Marketing Page and then on the Offer Page—and, consequently, conclude that their membership is cancelled. However, these two clicks would only get the subscribers to the Iliad Cancellation Page, which still requires another confirmation of intent to cancel. Navigating away from Amazon at this point or closing their browsers would place these subscribers in the "No Page" group, opening up the possibility that some of them may have mistakenly believed that they successfully cancelled their subscription. Similarly, some consumers who navigated to the Prime Central Page, and are grouped in the "Prime Central" category, may have mistakenly believed they had successfully cancelled their subscription.

(117) Subscribers who clicked Remind Me Later may have had an intent to cancel in the future but may have been unsuccessful in doing so. Subscribers who clicked the Keep My Benefits/Keep My Membership buttons on the Marketing Page or Offer Page may have mistakenly believed that these choices allow them to retain their Prime *benefits* without incurring ongoing *subscription* charges. Moreover, as I also discussed in Section II.E, research supports the possibility that such people may have become overwhelmed and acted in ways that do not reflect their original intent. For example, Schwartz (2004) studies how complex choices can lead to decision fatigue, errors, or inaction.[102] Mathur, Acar, and Friedman, M., et al. (2019) examine how websites use deceptive techniques to retain users or manipulate their choices.[103]

(118) In this section, I establish that the usage behavior of some subscribers who left the Iliad process through an action other than "Accept an Offer" indicates that they likely believed, mistakenly, that they had successfully cancelled their subscription. The key logic is that subscribers who mistakenly thought they had cancelled would not actively use their Prime benefits or would use them to a lesser extent than those in the Accept an Offer group.[104]

(119) To analyze economic harm from unsuccessful cancellations by users who likely thought they had cancelled, I start with a sample of about [redacted] unique subscriptions among about [redacted] Prime subscribers who entered the Iliad process and exited it without cancelling or pausing their membership during their first entry to the process. These are subscribers from the [redacted] sample, described in Section II.D, who entered the Iliad process between July 2019 and June 2023.[105] I define the *pre-entry* window as the period that starts 90 days before the subscriber enters the Marketing Page of the Iliad process (or the day after enrollment if that occurs within 90 days) and continues to 5 days prior to first entry into the Iliad process. I define the *post-entry* window as the period that starts 5 days after the subscriber enters the Iliad process and ends 90 days after they entered the process or when they next enter the Iliad process (if that occurs within 90 days). The 90-day window is chosen to balance the objectives of having long enough pre- and post-periods to meaningfully measure activity but short enough periods to measure activity in the vicinity of Iliad entry.[106] In my baseline analysis, I

102 Barry Schwartz, *The Paradox of Choice: Why More Is Less* (New York: HarperCollins, 2004).

103 A. Mathur, G. Acar, M. Friedman, E. Lucherini, J. Mayer, M. Chetty, and A. Narayanan, "Dark Patterns at Scale: Findings from a Crawl of 11K Shopping Websites," in *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (New York: Association for Computing Machinery, 2019): 1–14.

104 As explained in Section II.A, it is possible for subscribers to have some Prime benefit use without realizing that they are still subscribed to Prime.

105 Amazon provided data on all Iliad process entries between July 2019 and June 2023 ("cancellation process" data). I match the subscriber identification numbers in the [redacted] sample data to the cancellation process data and obtain a sample of subscribers who entered the Iliad process for whom the [redacted] sample data provide information on benefit use.

106 This restriction does not necessarily equalize the number of days pre- and post-Iliad entry for each subscription period, but it ensures that subscription days more than 90 days away from Iliad process entry are removed from the data. For example, if two subscribers were both in Prime for 120 days before starting the cancellation process for the first time and subscriber A successfully cancelled (thereby ending their subscription) 20 days after entering the Iliad process while

exclude activity in a 5-day window around the first Iliad entry because a subscriber's activity near the date of entry into the Iliad process may differ from typical Prime utilization.

(120) To investigate patterns of Prime benefit usage across the groups of subscribers who took different actions that resulted in incomplete cancellations, I calculate the shares of their subscriptions with no benefit usage before and after they entered the Iliad process. Figure 28 presents these shares, separately for usage of Prime shipping benefits and all Prime benefits.

(121) Subscribers who accepted an offer in the Iliad process had a lower share of subscription periods with no benefit usage post-entry relative to pre-entry; in contrast, other groups of subscribers that did not complete cancellation had greater shares of subscription periods with no benefit usage post-entry relative to pre-entry. This is true whether usage is measured based on Prime shipping benefits or all Prime benefits. For example, the percentage of zero shipping benefit usage subscription periods [redacted] by [redacted]% among subscribers who accepted an offer but *increased* by [redacted]% among subscribers in the "No Page" category (i.e., subscribers who closed their browsers or did not take any action for at least 2 hours on an Iliad screen). In other words, not using Prime shipping benefits became sharply more common among subscribers in the "No Page" group after they attempted to cancel.[107] The increase in non-use of benefits is similar when I measure usage based on all Prime benefits.

subscriber B remained a subscriber for another 120 days, the subscription days for these two subscribers that would remain in the data would be the 90 days before Iliad entry for each, the 20 days of post-Iliad entry for subscriber A, and the 90 days of post-Iliad entry for subscriber B. I also exclude the day of enrollment and day of cancellation.

107 The increase in the share of subscribers in the "No Page" category with zero benefit use post-entry is statistically significant (p-value < 0.05).

Figure 28: Share of subscriptions with zero benefit usage by action group, for Prime shipping benefits and all Prime benefits

Action	Prime shipping benefit usage			All Prime benefits usage		
	Share of subscriptions with no use pre-entry	Share of subscriptions with no use post-entry	% difference	Share of subscriptions with no use pre-entry	Share of subscriptions with no use post-entry	% difference
Accept an Offer	[redacted]					
No Page						
Prime Central						
Remind Me Later						
Keep My Benefits/Keep My Membership						
Other						

(122) These Prime benefit usage patterns across different groups of subscribers that did not complete cancellation suggest that some subscribers exit the Iliad process with the mistaken belief that they successfully cancelled their Prime subscription. These patterns also show that the actions subscribers take within the Iliad process are related to their benefit usage after they exit the process. Compared to subscribers who exited the cancellation process by accepting an offer, and therefore likely knew they remained subscribers, other groups exhibit a higher share of periods with no Prime benefit usage post-entry. This is consistent with the simple logic that subscribers would not use benefits they think they no longer have. The model I build in the next section to quantify economic harm from unsuccessful cancellations in which subscribers mistakenly believed they had cancelled builds on the differences in Prime benefit usage over time across different action groups.[108]

IV.C. Estimating harm from unsuccessful Amazon Prime cancellations

(123) In this section, I estimate the number of subscribers that exited the Iliad process with the mistaken belief that they cancelled their subscription. As described above, this does not capture the full extent of potential harm from Amazon's cancellation process because, for example, it does not include subscribers who never enter the Iliad process due to difficulties locating it or enter and who get frustrated or discouraged and exit with the correct belief that, despite their desire to cancel, they have failed to do so. An additional conservative step is that I exclude customers who exited the Iliad process via clicking on Remind Me Later or Keep My Benefits/Keep My Membership, because these customers may be less likely to have mistakenly thought they cancelled their Prime subscription.

[108] For brevity, in this section, I will refer to these customers as "unsuccessful cancellers" (even though some other types of customers may have tried to cancel and failed, but with knowledge that they had not cancelled).

Even so, some of these users may have been harmed because they expressed an intent to cancel and never accepted an offer from Amazon, yet continued paying for a Prime subscription. Indeed, as I show above, these groups also show post-entry increases in the proportion of subscriptions with no usage of Prime benefits.[109]

(124) In the first subsection below, I use a difference-in-differences regression in which subscribers who accepted an offer in the Iliad process are the "control" and subscribers who fall in the "No Page" group are the "treatment" to estimate the share of subscribers in the "No Page" group who exited the Iliad process with the mistaken belief that they cancelled their subscription. I run the same regression for the "Prime Central" action group (but, as described above, not for the "Remind Me Later" or "Keep My Benefits/Keep My Membership" groups). The results are statistically significant and establish economic harm from unsuccessful cancellations where customers believed they had cancelled. In the second subsection, I use the results of this analysis to estimate the number of harmed subscribers in the broader population due to unsuccessful cancellations and the dollar value of harm stemming from their additional Prime monthly fees payments.

IV.C.1. Subscribers' benefit usage after unsuccessful cancellations can be used to estimate harm

(125) As explained above, I view subscription periods with zero Prime benefit usage after an incomplete cancellation as an indicator of subscribers who intended to cancel. A mistaken belief that a subscription had been cancelled is one reason usage might fall to zero after entering and leaving the cancellation process. However, it is also possible that consumers who leave the Iliad process subsequently have zero Prime benefit usage for other reasons, such as shopping in-person or travel. Therefore, to estimate the share of subscribers who mistakenly believe they have cancelled Prime, I use a difference-in-differences regression analysis to measure the increase in the percentage of subscriptions with zero Prime benefit usage in the "No Page" group over and above the corresponding increase among subscribers who accepted an offer, while controlling for other factors that may affect Prime benefit usage. I conduct the same analysis for the "Prime Central" action group.

(126) Difference-in-differences regressions are a standard statistical analysis for establishing the impact of an event (in this context, unsuccessful cancellation) on an outcome (Prime benefit usage) and for

[109] As an illustration, consider a subscriber who would like to cancel because they do not expect to use Prime benefits in the future. The subscriber enters the cancellation process, becomes frustrated or overwhelmed, selects Remind Me Later or Keep My Benefits, and then forgets or does not notice the reminder email from Amazon and so continues paying for Prime. Because this type of subscriber did not expect to use Prime benefits moving forward, they would have been more likely to have zero usage after entering the Iliad process even if knew they had not successfully cancelled. (As Figure 27 shows, more users exit via Remind Me Later rather than Keep My Benefits/Keep My Membership, with the former accounting for [redacted]% of subscription periods among subscribers who enter the Iliad process but do not cancel and the latter accounting for [redacted]%.)

quantifying the extent of that impact.[110] For example, to estimate the impact of a policy intervention to reduce absenteeism in a given school district, it is not sufficient to measure the decrease in absenteeism in the school district that received the policy intervention. This is because absenteeism might be falling in all school districts, whether they received the policy intervention or not, due to, say, post-Covid trends in school attendance that are unrelated to the policy. Therefore, to establish that the policy intervention had an impact on absenteeism, it is necessary to statistically test whether absenteeism decreased in the school that received the policy intervention by significantly more than in other school districts. Using the same logic, establishing that some subscribers in the "No Page" or "Prime Central" groups had zero Prime benefit use due to their unsuccessful cancellation requires showing that they had a post-entry increase in zero benefit usage over and above the corresponding change for subscribers who were not "treated" with unsuccessful cancellation (i.e., those who accepted an offer). This is what the difference-in-differences regression measures.

(127) To account for various other factors that could affect the change in the share of zero benefit users in the control and treatment groups, I also include variables that capture each subscriber's signup method, signup quarter-year, and quarter-year of entry to the Iliad process.

(128) To measure pre- and post-entry usage, I focus on shipping benefits only and apply the same restrictions discussed above (remove the first and last day of each subscription, remove any benefit use 5 days before or after entry into the Iliad process, and remove any usage outside of the 90-day window around Iliad entry).

(129) Figure 29 presents the results, which are all statistically significant and show that both the No Page and the Prime Central groups had significant increases in the frequency of zero benefit usage post-entry into the cancellation process.[111] For example, the coefficient estimate of [redacted] indicates that subscriptions in the No Page group are, on average, [redacted] percentage points more likely to have zero benefit usage post-Iliad entry *relative to* the control group of Accept an Offer. The [redacted] coefficient for the Prime Central group has the same interpretation.

[110] Joshua D. Angrist and Jörn-Steffen Pischke. *Mastering 'Metrics: The Path from Cause to Effect* (Princeton, NJ: Princeton University Press, 2015).

[111] The coefficients are statistically significant at the [redacted]% level. The results in Figure 29 and Figure 30 are based on defining zero benefit usage based on a 90-day window pre- and post- entry into the cancellation process but excluding the five days before and after entry. For results without the 5-day window excluded, which are similar, see Appendix E.1.

Figure 29: Difference-in-differences estimates of the increase in zero benefit usage for the No Page and Prime Central action groups

Treatment group	Coefficient
No Page	[redacted]
Prime Central	[redacted]

Note. Results are based on usage in up to 90-day windows around the date of cancellation process entry, with the 5 days pre- and post-entry excluded.

IV.C.2. Estimating harm, in the form of additional Prime fee payments, from unsuccessful cancellations of Prime subscriptions

(130) In this section, I calculate the economic harm sustained by Prime subscribers who exited the Iliad process with the mistaken belief that they cancelled their memberships. The difference-in-differences regression results provide an estimate of the share of subscriptions in each action group that were harmed by an unsuccessful cancellation where they believed they had cancelled. These unsuccessful cancellations will result in subscribers continuing to pay Prime fees for benefits they believed they no longer had access to.

(131) Amazon's customer data provide the amounts that each subscriber paid in Prime fees during a subscription period. To calculate the economic harm to subscribers who continued to pay for benefits they did not intend to retain, I calculate the total payments by subscribers in each treatment group starting one day after the date of their entry into the Iliad process. This date restriction ensures that harm from unintentional enrollment is not double counted with harm from unsuccessful cancellation.[112] I also exclude all payments a subscriber makes after entry into the Iliad process for a second time, since a cancellation attempt may indicate awareness that the subscriber's Prime membership was not cancelled. This approach is conservative in that customers who enter the Iliad process a second time may experience similarly difficulty cancelling their subscriptions and would continue to be harmed by the Iliad process. In the same vein, as discussed above, the harm calculations are conservative in that they do not include additional Prime fees paid by subscribers who desired to cancel but had difficulty locating the Iliad process or exited the process in frustration. Insofar as subscribers in other action groups similarly exited the Iliad process with a mistaken belief that they had cancelled, the resulting Prime payments are also not included in these calculations.

(132) Calculating total payments by subscribers in the No Page and Prime Central action groups, multiplying this sum by each group's corresponding difference-in-differences regression coefficient, and extrapolating this sum to the full population of Prime subscribers yields the estimated dollar harm for each group. See Figure 30. As reported in the first row, the [redacted]% of subscribers in the No Page group with unsuccessful cancellations (relative to the control group) had $101 million in Prime fee

[112] Harm for unintentional enrollment includes payments made until and including the day they entered the Iliad process.

payments after their entry into the Iliad process (subject to the data exclusion conditions described above). The corresponding estimate for the Prime Central group is $23.0 million.[113]

Figure 30: Harm estimates for unsuccessful cancellers, No Page and Prime Central action groups

Action group	Additional Prime fee payments after unsuccessful cancellation ($M)
No Page	$101
Prime Central	$23

Note. Results are based on the product of total Prime payments and the difference-in-differences estimates in Figure 29 for each group. Payments are limited to those made after December 29, 2018, and exclude fees after subsequent cancellation process entry.

IV.C.3. Additional requested calculations related to cancellation process entries and payments

(133) As noted above, the preceding calculations exclude all payments subscribers make after entry into the Iliad process for a second time, on the grounds that a second entry into the cancellation process may have indicated awareness at that point that the subscriber's Prime membership was not cancelled. The FTC has indicated that, as a legal matter, it may be appropriate to measure harm on the basis of all Prime fees paid by these subscribers after the date on which they first entered the Iliad process, meaning to calculate the dollar harm from additional Prime fees without excluding payments after subscribers' second entry (and all subsequent entries) into the Iliad process.[114] The calculations are otherwise identical to the preceding calculations. The results are in Figure 31.

Figure 31: Harm estimate for unsuccessful cancellers, without excluding Prime fees after subsequent cancellation process entry, No Page and Prime Central action groups

Action group	Additional Prime fee payments after unsuccessful cancellation ($M)
No Page	$116
Prime Central	$26

Note. Results are based on usage in up to 90-day windows around the date of cancellation process entry, with the 5 days pre- and post-entry excluded. Limited to payment made after December 29, 2018.

(134) The FTC has also requested that I provide the following additional calculations:

113 Appendix E.2 contains the corresponding figures based on alternative cutoff dates and limiting to cancellation entry dates after the cutoff date.

114 Appendix E.3 contains the corresponding figures based on alternative cutoff dates and limiting to cancellation entry dates after the cutoff date.

1. The number of subscriptions in which a subscriber entered the Iliad cancellation process but did not cancel their Prime membership and the total fees paid by those subscribers thereafter until a successful cancellation, if any.
2. The number of subscriptions among subscribers in category (1) who also had a decline in Prime benefits usage after entering the cancellation process (compared to their own prior usage), and their total subsequent Prime payments until successful cancellation, if any.[115]
3. The difference-in-difference estimates for five action groups—No Page and Prime Central (as in Figure 31) as well as Keep My Benefits/Keep My Membership, Remind Me Later, and Other.

(135) The results are in Figure 32. Where relevant (panels 2 and 3) all variations are based on measuring usage in up to 90-day windows before and after the date of entry into the cancellation process, with the 5 days pre- and post-entry excluded. The post-entry fee totals in the final column reflect all Prime fee payments after the date of entry until successful cancellation, if any.

Figure 32: Subscriptions and post-entry Prime payments among subscribers who enter the cancellation process but do not cancel, by action group (limited to fees paid after December 29, 2018)

Scenario	Action group	Count of subscriptions (M)	Prime fee payments post-cancellation process entry ($M)
1. Cancellation process entries	No Page	[redacted]	$457
	Prime Central		$119
	KMB/KMM		$273
	Remind Me Later		$143
	Other		$267
2. Cancellation process entries with flat or decreased subsequent Prime benefits usage	No Page		$201
	Prime Central		$46
	KMB/KMM		$100
	Remind Me Later		$54
	Other		$75
3. D-I-D estimates (vs. Accept an Offer)	No Page		$116
	Prime Central		$26
	KMB/KMM		$67
	Remind Me Later		$31
	Other		$27

115 This necessarily includes the number of subscriptions among subscribers in category (1) who had zero benefits usage after entering the cancellation process, and their total subsequent Prime payments until successful cancellation, if any.

V. Dr. Kivetz does not substantiate his criticisms of the Cancellation Survey and, in any case, his claims do not impact my opinions

(136) As I explained in Section V.A above, Amazon's Cancellation Survey provides a reliable basis to draw inferences regarding the behavior of its customers, and the Cancellation Survey is reliable and appropriate to use to evaluate unintentional enrollment in Prime.

(137) In his report, Amazon's expert Dr. Kivetz argues that the results of Amazon's Cancellation Survey are "completely uninformative, unscientific, and unreliable with respect to whether (and how many) customers in fact intentionally signed up for Prime."[116] He offers three primary justifications for his claim.[117]

1. According to Dr. Kivetz's "Opinion A," Amazon's design and execution of its Cancellation Survey suffered from numerous, serious flaws such that the Survey does not meet "rigorous, accepted scientific standards and principles."[118]
2. According to Dr. Kivetz's "Opinion B," the Survey response patterns are not logically consistent and show that respondents chose the "I did not intend to sign up for Prime" ("DNI") option at artificially inflated rates due to "uncontrolled guessing."[119]
3. According to Dr. Kivetz's "Opinion C," even if the Survey results were (according to Dr. Kivetz, inappropriately) used to investigate potential unintentional enrollment, the data show that Amazon's Prime upsells were extremely unlikely to result in unintentional enrollment.[120]

(138) The remainder of this section contains my responses to Dr. Kivetz. As I explain below, Dr. Kivetz's claim that the Cancellation Survey is "completely uninformative, unscientific, and unreliable" is not substantiated and his arguments against the Survey do not impact my use of the Survey or my opinions.

[116] Kivetz Report, ¶ 22. While Dr. Kivetz criticizes aspects of Amazon's Cancellation Survey, Dr. Kivetz's arguments do not rule out unintentional enrollment or consumer harm from Amazon's practices.

[117] Kivetz Report, ¶ 22. Dr. Kivetz provides two additional opinions: "Opinion D" on Customer Service Call data and "Opinion E" on Amazon's "Search Sentiment" Survey. Both opinions are unrelated to the Cancellation Survey.

[118] Kivetz Report, ¶ 22.

[119] Kivetz Report, ¶ 22. Dr. Kivetz refers to the "I did not intend to sign up for Prime" answer choice using the abbreviation "DNI."

[120] Kivetz Report, ¶ 22.

V.A. Dr. Kivetz's claims about Amazon's flawed design and execution of the Survey are inconsistent with Amazon's actions and standard scientific practice

(139) As an initial matter, Dr. Kivetz's claims are inconsistent with Amazon's own use of the Survey.

- As discussed in Section III.A.1, Amazon designed, invested in, and refined its Cancellation Survey to provide it with business intelligence about its customers. Amazon used it to inform decisions with material business consequences.[121] Notably, the Cancellation Survey was not an outside survey designed by a third party but instead was internal Amazon business intelligence.
- Amazon had multiple opportunities to abandon the Survey since 2018 if it did not provide useful business-relevant information, but Amazon chose not to. In early 2020, two years after the Survey first launched, Amazon added additional questions and expanded the Survey worldwide.[122] In November 2022, Amazon added two more questions regarding consumers' intention to rejoin Prime (Questions 9 and 10).[123]
- Similar to my analyses of unintentional enrollment in Section III, Amazon also used the Survey results for its own "unintentional signup deep dive."[124]

(140) Amazon's Survey uses accepted principles and the extensive checklists referenced by Dr. Kivetz, mainly for surveys prepared for litigation, do not reflect standard research practices for economic analysis that can validate the survey with observational data.[125]

(141) Amazon's Survey follows standard practices that increase survey validity. The invitation to complete the Survey is randomly assigned to cancellers. Questions 3 and 4 include an "other" category, and Question 4 includes an additional "No, there were no other reasons" answer, so as not to force respondents to guess if their actual reason for cancelling is not listed. Following best practices, responses for Questions 1 and 2 are displayed in a fixed, highest to lowest ordering, while responses for Questions 3 and 4 have their order randomly assigned.[126]

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121 *See, e.g.*, AMZN_00059329–334.

122 AMZN_00001517; AMZN_00001500.

123 Kivetz Report, ¶ 27; AMZN-PRM-FTC-DATA-00000017.

124 AMZN_00041335.

125 *See* the discussion in Section III.A.

126 *See, e.g.*, Shari Seidman Diamond, "Reference Guide on Survey Research," in *Reference Manual on Scientific Evidence: Third Edition* (Washington, DC: The National Academies Press, 2011): 395–396. *See also* Section III.A.

V.B. Dr. Kivetz makes numerous assertions about the Cancellation Survey that are not supported by the data

(142) Dr. Kivetz claims that Amazon's design and execution of its Cancellation Survey suffered from numerous, serious flaws such that the Survey does not meet "rigorous, accepted scientific standards and principles."[127] Dr. Kivetz concludes the Cancellation Survey "*cannot* be relied on to reach scientific and valid conclusions about alleged unintentional enrollment," stating that "the results of the Cancellation Survey are completely uninformative, unscientific, and unreliable with respect to whether (and how many) customers in fact unintentionally signed up for Prime."[128]

(143) A number of Dr. Kivetz's claims are untested assertions for which he offers no empirical support. In the remainder of this section, I offer several examples of claims by Dr. Kivetz that are inconsistent with the available data. These examples highlight the unsupported nature of Dr. Kivetz's assertions.

V.B.1. Dr. Kivetz's claim that the Cancellation Survey's sample will lead to an overestimate of DNI responses is incorrect

(144) Dr. Kivetz argues that the Cancellation Survey "fails to represent not only the universe of Amazon Prime members who cancel their memberships but also the relevant universe of all consumers who encountered the challenged enrollment flows."[129] He concludes that "[t]he survey's sample is likely to severely overestimate the rate of 'DNI' responses among the population of Prime cancelers, let alone of the relevant universe of all consumers exposed to a Prime enrollment flow."[130]

(145) Contrary to Dr. Kivetz's claim, my Survey-based estimates of unintentional enrollment have a number of features that may lead to an *underestimate* of the universe of unintentional enrollments.

- The Survey is only applied to subscribers who cancelled, and therefore excludes subscribers who did not intend to enroll but have not realized that they are enrolled.[131]
- The Survey is only offered to subscribers who cancelled online, and not those subscribers who cancelled by phone or other means. An Amazon internal document references some customers

[127] Kivetz Report, ¶ 22, Opinion A.

[128] Kivetz Report, ¶ 45 (emphasis in original).

[129] Kivetz Report, ¶ 69.

[130] Kivetz Report, ¶ 79.

[131] AMZN_00080322–323 ("One insight from UX research, surveys, and Customer Service is that customers do not always check their bills. This causes some to go through multiple billing cycles before they realize there is a problem (assuming they ever recover)…surveys on customers' awareness of their Prime status show that a [redacted] percentage of active Prime members are unaware or uncertain about their membership status. For example, when surveyed, [redacted] of 9-month-tenured members in France incorrectly reported they were not a member…it is important to consider that CS impacts only capture the customers who know there is a problem to contact us about…there appear to be segments of customers who are not aware of their membership status, but who are not canceling and/or contacting us about it in a timely fashion (if at all).").

contacting customer service by phone for "cancellations due to unintended sign-ups"—any such unintentional enrollees will not be reflected in the Survey data or included in my harm calculations.[132]

- The Survey asked for the reasons for cancellation. There may plausibly be customers who did not intend to subscribe but, having subscribed, cancelled for another reason. These unintentional enrollees would not be reflected in the Survey.
- Even if some of Dr. Kivetz's claims of potential sources of upward bias of DNI rates were valid, he has not provided evidence on the quantitative importance of these sources, and further has not provided any evidence that these sources of upward bias are large enough to offset sources of downward bias listed above.

(146) To examine Dr. Kivetz's self-selection and negative bias claim, I analyze Amazon's data from the Cancellation Survey. If one assumes there was negative bias (i.e., that Survey respondents were more likely to have negative attitudes about Amazon), one might expect Survey respondents to have lower benefit usage than the population of customers who were invited to take the Survey. The figures below show no evidence of this claim. For all Prime benefits use and Prime shipping benefits use, Survey respondents have similar utilization to the broader population of Survey pop-up recipients (both customers who did and did not take the Survey). These patterns do not support Dr. Kivetz's claim that "self-selected" Survey respondents are different from the overall [redacted]% of Prime subscribers who cancelled online and who Amazon randomly chose to offer the Survey.[133]

[132] AMZN_00080322.

[133] Even if the Survey respondents were different from the overall population in some respects, that would not establish that the DNI rate from the survey is biased upward.

Figure 33: All Prime benefit usage days by subscription length

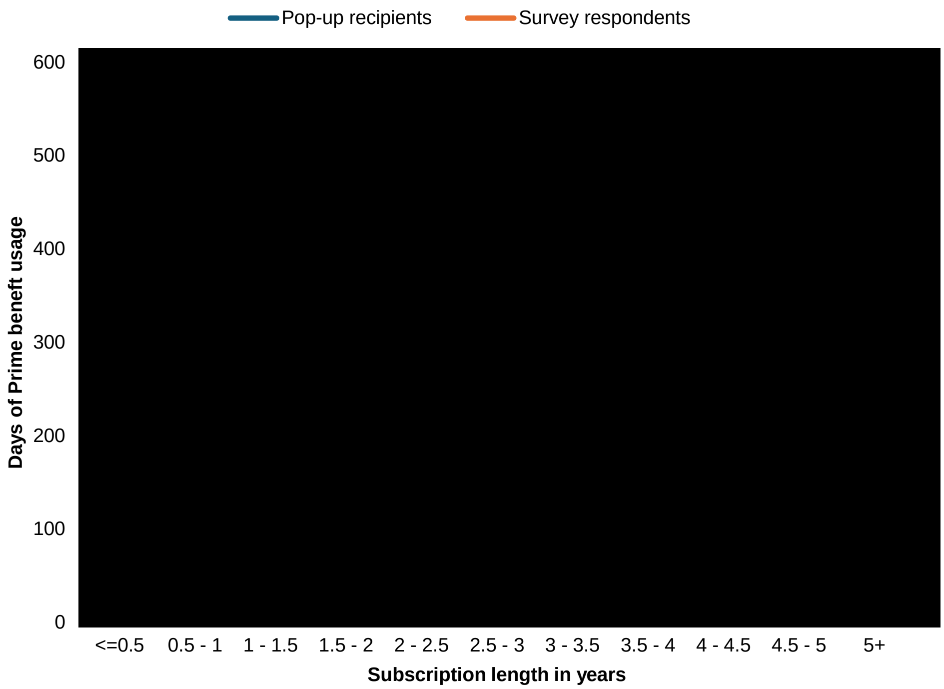
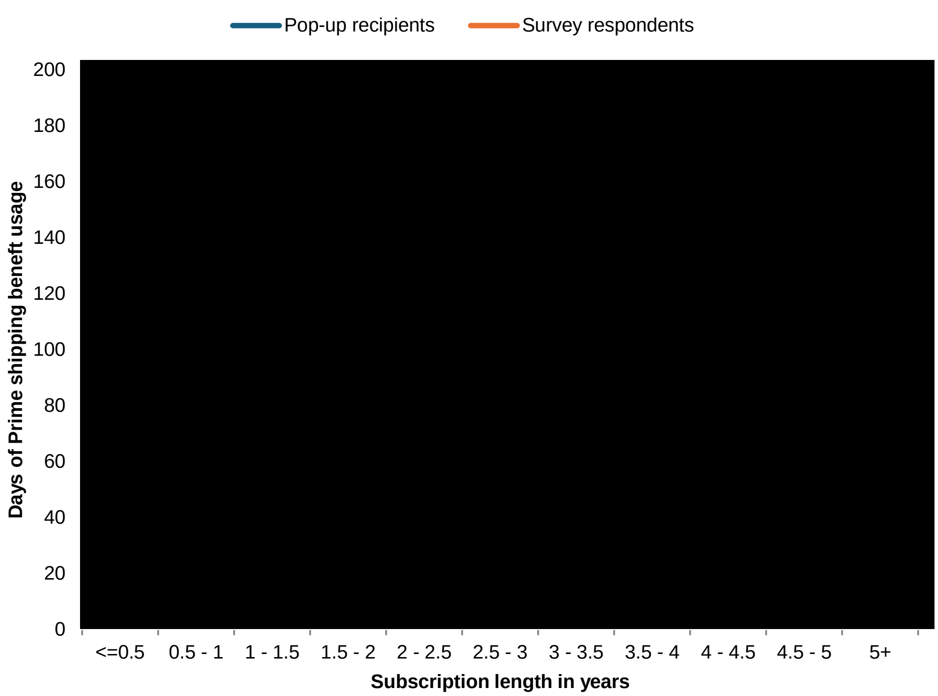


Figure 34: Prime shipping benefit usage days by subscription length



V.B.2. Dr. Kivetz's assertion of bias due to the design and timing of the Cancellation Survey is unsupported and inconsistent with the Survey results

(147) Dr. Kivetz argues that the use of the Cancellation Survey to assess unintentional enrollment is inappropriate because the Survey "was designed to test issues regarding customers' satisfaction and dissatisfaction with Prime **at the time of cancellation**, *not their mindsets at the time of enrollment*" and that "[r]esponses of 'DNI' in the Cancellation Survey are susceptible to acute memory biases."[134]

(148) Yet, despite offering this criticism, Dr. Kivetz also generally criticizes the Survey's use of closed-ended questions for assessing consumers' reasons for cancellation and argues that "**open-ended questions** —and **not** closed-ended questions—are the appropriate format to measure consumers' reasons for cancellation."[135] Open-ended questions involve a greater use of recall than closed-ended questions, and thus may be more susceptible to memory errors or bias.[136]

(149) Dr. Kivetz's conjecture that potential "memory bias" may lead to overstated DNI responses is inconsistent with the actual Survey responses. In fact, any bias may be in the opposite direction. As shown in the figure below, respondents with a longer time lag between enrollment and cancellation are less likely to select DNI, not more as Dr. Kivetz suggests.

[134] Kivetz Report, ¶¶ 56–57 (emphasis in original). As I discussed in Section III.A.2, economic research on the relationship between length of recall and accuracy of survey responses shows mixed results.

[135] Kivetz Report, Section A.4.2.1 (emphasis in original).

[136] *See* Shari Seidman Diamond, "Reference Guide on Survey Research," in *Reference Manual on Scientific Evidence: Third Edition* (Washington, DC: The National Academies Press, 2011): 392 fn.148 ("An open-ended question presents the respondent with a free-recall task, whereas a closed-ended question is a recognition task. Recognition tasks in general reveal higher performance levels than recall tasks. Mary M. Smyth et al., Cognition in Action 25 (1987). In addition, there is evidence that respondents answering open-ended questions may be less likely to report some information that they would reveal in response to a closed-ended question when that information seems self-evident or irrelevant.").

Figure 35: Share of DNI responses across subscription length (UPDP)

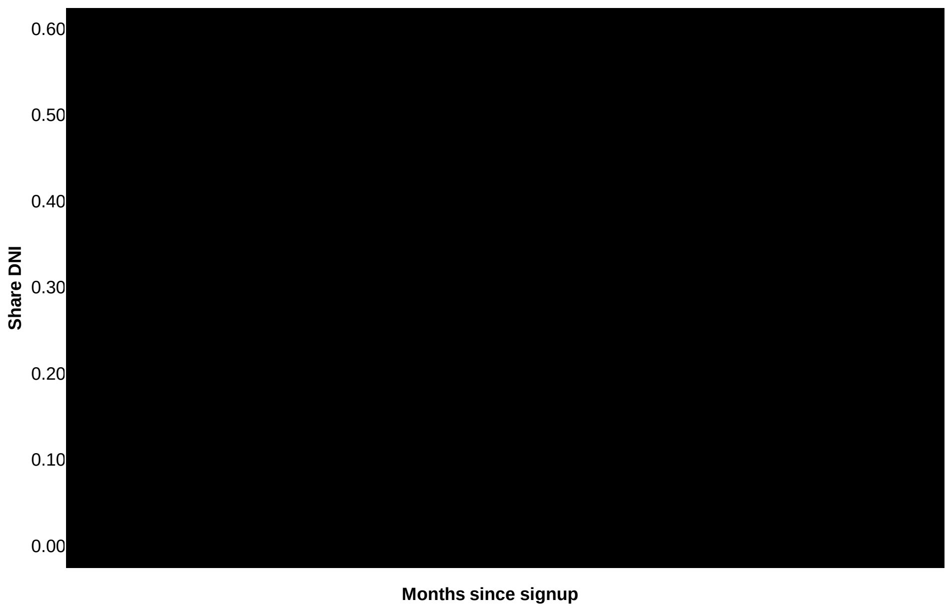


Figure 36: Share of DNI responses across subscription length (SPC)

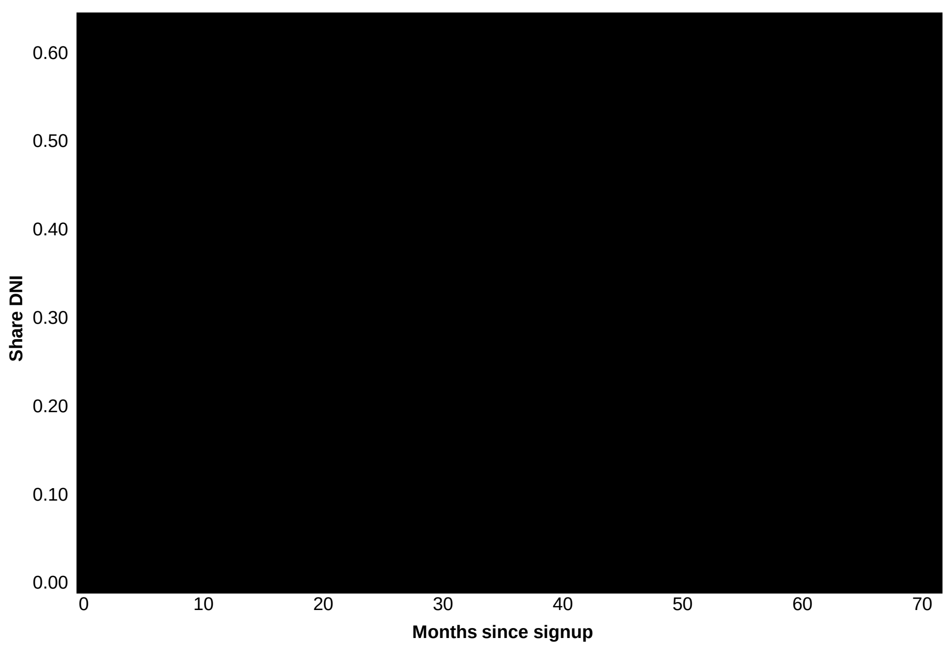
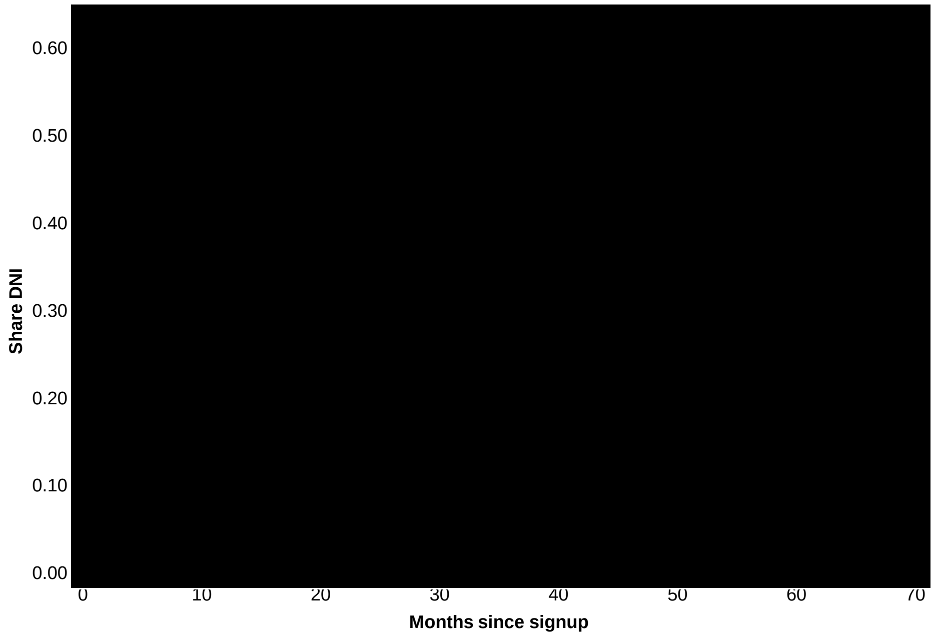


Figure 37: Share of DNI responses across subscription length (SOSP)



(150) Dr. Kivetz argues that the Survey suffers from other forms of bias, such as demand effects and order biases. I disagree. The Cancellation Survey questions were clear and non-leading, and encounters with the "did not intend" responses were minimized, addressing concerns about demand effects.[137] The randomized order of the pre-populated answers (aside from "Other," which is always last) addresses potential order bias from respondents more frequently selecting the responses at the top of the list. Dr. Kivetz's bias claims also apply to the other responses, not just DNI so his claims provide no reason to expect DNI responses to be inflated.

(151) More generally, Dr. Kivetz provides no evidence of bias and crucially no evidence that on net any bias leads to inflated DNI responses. In addition, Dr. Kivetz ignores the possibility of bias that could lead respondents to understate DNI.

(152) As mentioned above, the timing of the Survey may lead to an underestimate of DNI rates. Customers who originally did not intend to enroll may have cancelled for other reasons and thus may not report DNI in the Survey.

(153) The Cancellation Survey asks customers about a recent event, as it is initiated immediately after their just-completed cancellations. Most of the potential responses relate to issues that would be recent for many customers who cancel (e.g., "experienced a problem," "fee was too expensive," "not making

[137] The "did not intend" response is removed from Question 4 if it was selected in Question 3, as is the case for the other responses. Question 7 includes a "did not intend" response, but not all respondents reach that question (in addition, I do not use Question 7 responses to identify unintentional enrollment). Kivetz Report, ¶¶ 33–34.

enough purchases"). One response, "did not intend," would often refer to a less immediate event—the start of enrollment—for many customers. If it were the case that respondents' memories of more distant events are poorer, that would likely skew them away from selecting the response that references the past, which would understate the true frequency of "did not intend."

(154) The Survey was pitched to appeal to goodwill, potentially selecting on consumers with a good experience. Specifically, as shown in Figure 13, the Survey pop-up stated, "Help us improve our services by taking a quick 2-minute survey." This type of self-selection, if it exists, would bias DNI rates downward.

(155) Refund-seeking behavior could bias respondents away from selecting DNI. For instance, a consumer seeking a refund might select "I experienced a problem with Prime (e.g., delivery issue, customer service problem, etc.)" if they thought that Amazon would provide a refund to remedy a problem they experienced with Prime.

(156) There is no reason to think the Survey respondents lied when responding to the Survey, based on the academic literature. Lundquist, Ellingsen, Gribbe, and Johannesson (2009) find that individuals have an aversion towards lying about private information and that the aversion to lying increases with the size of the lie.[138] Similarly, Erat and Gneezy (2012) find that the cost of lying is high and that players are unwilling to lie even when doing so would have helped other players.[139] Gneezy, Rockenbach and Serra-Garcia (2013) find a considerable aversion to lying, which strategic considerations cannot explain.[140] Given that people are averse to lying even in situations where they have monetary incentives to do so, it seems reasonable to assume that they would also be averse to lying when voluntarily responding to survey questions.

(157) Amazon's conduct prevented the implementation of a signup survey that could directly inform enrollees that they had signed up—a measure that would have mitigated concerns about awareness bias.

V.B.3. Dr. Kivetz's claim that "The Observed Rate of 'DNI' Responses is Artificially Inflated Due to Uncontrolled Guessing" is rejected by the Survey results

(158) According to Dr. Kivetz, "[d]ue to guessing alone, the [redacted]% rate of 'DNI' selections cannot be taken at face value, because a non-trivial proportion (or a considerable proportion, or perhaps even the

[138] Tobias Lundquist, Tore Ellingsen, Erik Gribbe, and Magnus Johannesson, "The Aversion to Lying," *Journal of Economic Behavior & Organization* 70, no. 1–2 (2009): 81–92.

[139] Sanjiv Erat and Uri Gneezy, "White Lies," *Management Science* 58, no. 4 (2012): 723–733.

[140] Uri Gneezy, Bettina Rockenbach, and Marta Serra-Garcia, "Measuring lying aversion," *Journal of Economic Behavior & Organization* 93 (2013): 293–300.

majority) of such selections are likely to be 'false positives'—that is, reflecting respondents who happened to check the 'DNI' answer box even though they in fact intentionally enrolled in Prime."[141] Dr. Kivetz attempts to support this claim with hypothetical calculations purporting to show that respondent guessing led to significant inflation in the rate of 'DNI' responses.[142]

(159) Dr. Kivetz's guessing critique is rejected by the data. I estimate an upper bound for the share of random guessing behavior that could be present in the Cancellation Survey responses. I first restrict to the Survey respondents who selected the answer to Q3 with the lowest share of answers. That answer happens to be "I experienced a problem with Prime," and accounts for [redacted]% of the responses. I then further restrict to the people who did not take the time to type an answer to Q8. It is unlikely that all those who did not respond Q8 were guessing, but one can assume that people who took the time to type in an answer were not responding to other questions at random. This yields an estimated upper bound of [redacted]% of responses that could be consistent with guessing behavior per answer option. If I apply this upper bound, I calculate that guessing behavior could at most lower the [redacted]% of UPDP enrollees who provide a DNI response to Q3 to [redacted]% instead. For the reasons explained throughout this report, that is unlikely; in fact, the [redacted]% figure is more likely to understate the true DNI rate.

(160) In addition, to address the concern that people might be carelessly responding, or guessing, I focus on the Survey respondents who wrote an answer for Q8, an open-ended question towards the end of the Survey. Dr. Kivetz calculates his figure of [redacted]% DNI based on responses to Q3, Q4, and Q7. Among those who provided an answer for these three questions, a subset also wrote in an answer for Q8. These are respondents who took the time to type an answer to this open question rather than leaving it blank, which gives reason to believe that their answering was not careless. When restricting to this sample, in addition to same limitations applied by Dr. Kivetz, [redacted] chose DNI in either Q3, Q4, or Q7.[143] This is modestly higher than the [redacted]% reported by Dr. Kivetz, indicating that DNI rates are not biased upward by careless responding or guessing.[144]

(161) As shown in Figure 24, customers who selected DNI in the cancelation survey had lower rates of Prime benefit use. This is consistent with the DNI customers not being aware that they had a Prime subscription. It is inconsistent with considerable guessing on the survey; if customers are guessing, there would be no correspondence between survey responses and Prime benefits usage.

[141] Kivetz Report, ¶ 191.

[142] Kivetz Report, ¶¶ 196–205.

[143] Kivetz Report, ¶ 189.

[144] Using my definition of DNI based on just Q3 and Q4 (not including Q7), and applying Dr. Kivetz's data limitations, the resulting DNI share is [redacted]%.

V.B.4. The patterns identified by Dr. Kivetz are not evidence of inconsistency in the Survey responses

(162) Dr. Kivetz claims that the Survey results "show that respondents who selected 'DNI' also frequently selected other answer choices that call into question an interpretation of 'DNI' as evidence of true unintentional enrollment."[145] Dr. Kivetz presents "four categories of such apparent inconsistencies," concluding that these inconsistencies "raise serious doubts about the validity of survey responses *if one were to adopt* the FTC's apparent interpretation of 'DNI' response [sic] as representing unintentional enrollment."[146]

(163) Dr. Kivetz's argument about inconsistent Survey responses is misleading and based on a limited and narrowly scoped study of DNI respondents. First, comparing satisfaction between DNI and non-DNI respondents indicates lower satisfaction among DNI respondents, consistent with a greater degree of unintentional enrollment.[147] Second, behavioral inconsistencies do not invalidate unintentional enrollment. For example, consumers might appreciate the service after becoming aware of it but still report that they were misled about how they were enrolled.

(164) Third, in Section III.A.4, I explained how the correspondence between changes in DNI rates over time and Amazon's changes to increase the clarity of its UPDP upsells provides evidence in support of the reliability of the Survey. If Dr. Kivetz's claims of methodological errors, "guessing," negativity bias, or other issues that need to be "controlled for" were important, the changes in UPDP upsells would not translate into significant differences in DNI rates. However, I find that during September 17, 2020 through December 2, 2020, when Amazon made certain changes that it predicted would improve the "clarity" of the UPDP enrollment page, DNI rates declined by a statistically significant amount relative to the periods without the UPDP clarity improvements. Dr. Kivetz himself recognizes that the Survey could appropriately be used "to track general trends over time."[148]

(165) Fourth, the following figure shows DNI rates from Amazon's other cancellation surveys. The similarity of the DNI rates in these surveys to the DNI rate in the Cancellation Survey further supports the reliability of the Survey responses.

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145 Kivetz Report, ¶ 206.

146 Kivetz Report, ¶¶ 209, 227 (emphasis in original).

147 *See* Figure 19.

148 Kivetz Report, ¶ 22.

Figure 38: DNI response rates from other Amazon cancellation surveys

Survey	Survey period	Number of responses	DNI share
1	03/27/2020–05/16/2023	[redacted]	
2	11/07/2018–03/02/2019		
3	09/17/2018–07/19/2020		
4	11/07/2018–02/17/2019		
5	11/06/2018–03/05/2022		
6	11/06/2018–12/04/2021		
7	11/06/2018–06/02/2022		
8	04/03/2020–04/12/2023		
9	11/06/2018–04/02/2019		

V.B.5. Dr. Kivetz's claims regarding Amazon's Prime upsells are incorrect and do not invalidate my use of the Cancellation Survey

(166) Dr. Kivetz claims to analyze "the extent to which Amazon's allegedly deceptive Prime upsells were likely to result in instances of unintentional enrollment."[149] Dr. Kivetz offers calculations indicating "an approximately [redacted]% likelihood of an upsell resulting in an unintentional enrollment" while claiming that this [redacted]% rate is "highly conservative and overstated."[150] Dr. Kivetz concludes that "[t]his is an extremely [redacted] rate (less than [redacted]%), one that is inconsistent with the FTC's allegation that Amazon's Prime upsells deceived or misled customers into enrolling in Prime."[151]

(167) Dr. Kivetz estimates that [redacted]% of people who receive *any single* upsell—regardless of whether it is UPDP, SPC, or SOSP—will unintentionally enroll as a result of that upsell. Dr. Kivetz's [redacted]% estimate is irrelevant to my analysis, which examines how many people who actually enroll in Prime did so unintentionally. Dr. Kivetz, by contrast, is examining all instances of someone receiving an upsell, regardless of whether they enroll.

(168) Dr. Kivetz's analysis also inappropriately focuses on the probability of a single upsell leading to a potential unintentional enrollment.

- First, as explained above, a regular non-Prime Amazon customer will experience numerous upsells during their checkout processes. Even if Dr. Kivetz's [redacted]% estimate were correct, the probability that such a customer (who experiences numerous upsells) would unintentionally enroll would greatly exceed [redacted]%. For example, if non-Prime customers experience 30 upsells that each had a [redacted]% change of resulting in an unintentional enrollment, each customer would

[149] Kivetz Report, ¶ 237.

[150] Kivetz Report, ¶¶ 383, 385.

[151] Kivetz Report, ¶ 384.

have an overall [redacted]% chance of unintentionally enrolling (i.e., more than [redacted] such customers would unintentionally enroll).[152]

- Second, Dr. Kivetz's conclusion that his [redacted]% estimate is inconsistent with customers having been "deceived or misled" is illogical. Dr. Kivetz's claim is analogous to asserting that spam emails resulting in harmful fraud must not have been deceitful or misleading if the fraud rate per spam email sent is low.

152 [redacted]

______________________	March 24, 2025
Dr. Neale Mahoney	Date

Appendix A. Curriculum Vitae

A.1. Education

- PhD, Stanford University
- ScB, Brown University, summa cum laude

A.2. Academic positions

- Stanford University, Department of Economics, 2020–present
  - Professor of Economics, 2020–present
  - George P. Schultz Fellow at SIEPR, 2021–present
  - Trione Director of SIEPR, 2025–present
- University of Chicago Booth School of Business, 2013–2020
  - Professor of Economics, 2018–2020
    - David G. Booth Faculty Fellow, 2018–2020
  - Associate Professor of Economics, 2017–2018
    - David G. Booth Faculty Fellow, 2017–2018
  - Assistant Professor of Economics, 2013–2017
    - Robert King Steel Faculty Fellow, 2013–2014
    - Neubauer Family Faculty Fellow, 2014–2015
- Harvard University, 2011–2012
  - Robert Wood Johnson Scholar in Health Policy Research

A.3. Research affiliation

- George P. Shultz Fellow, Stanford Institute for Economic Policy Research (SIEPR), 2021–present.

- Research Associate, National Bureau of Economic Research, 2018–present (Faculty Research Fellow, 2012–2018).
- Affiliated Professor, J-PAL, 2020–present.
- Academic Research Council, Consumer Financial Protection Bureau, 2023–2025.

A.4. Editorial boards

- *American Economic Journal: Applied Economics,* Co-editor, 2019–2022.

A.5. Professional positions

- Special Policy Advisor for Economic Policy, White House National Economic Council, 2022–2023.
- Economist, Office of Management and Budget, 2009–2010.
- Academic Advisory Council, Brookings Institution Center on Regulation and Markets, 2019–2022.
- Co-Director, Health Economics Initiative, Becker Friedman Institute, 2018–2020.

A.6. Selected publications

A.6.a. Research papers in academic journals

- "The Effects of Medical Debt Relief: Evidence from Two Randomized Experiments." With Raymond Kluender, Francis Wong, and Wesley Yin. *The Quarterly Journal of Economics* qjae045 (2024).
- "Long-Term Care Hospitals: A Case Study in Waste." With Liran Einav and Amy Finkelstein. *The Review of Economics and Statistics* 105, no. 4 (2023): 745–765.
- "What Determines Consumer Financial Distress? Place- and Person-Based Factors." With Benjamin J. Keys and Hanbin Yang. *Review of Financial Studies* 26, no. 1 (2023): 42–69.
- "The Impact of Financial Assistance Programs on Health Care Utilization." With Alyce Adams, Ray Kluender, Jinglin Wang, Francis Wong, and Wes Yin. *American Economic Review: Insights* 4, no. 3 (2022): 389–407.

- "Financial Incentives to Facilities and Clinicians Treating Patients With End-stage Kidney Disease and Use of Home Dialysis: A Randomized Clinical Trial." With Yunan Ji, Liran Einav, and Amy Finkelstein. *JAMA Health Forum* 3, no. 10 (2022).
- "Principles for Combining Descriptive and Model-Based Analysis in Applied Microeconomics Research." *Journal of Economic Perspectives* 36, no. 3 (2022): 211–22.
- "Trends in Medical Debt During the COVID-19 Pandemic." With Ben Guttman-Kenney, Ray Kluender, Francis Wong, Xuyang Xia, and Wes Yin. *JAMA Health Forum* 3, no. 5 (2022).
- "Hospital Lawsuits Over Unpaid Bills Increased By 37 Percent In Wisconsin From 2001 To 2018." With Zack Cooper and James Han. *Health Affairs* 40, no. 12 (2021).
- "Voluntary Regulation: Evidence from Medicare Payment Reform." With Liran Einav, Amy Finkelstein, and Yunan Ji. *Quarterly Journal of Economics* 137, no. 1 (2022): 565–618.
- "The IO of Selection Markets." With Liran Einav and Amy Finkelstein. *The Handbook of Industrial Organization* 5, no. 1 (2021): 389–426.
- "Medical Debt in the US, 2009-2020." With Ray Kluender, Francis Wong, and Wes Yin. *JAMA* 326, no. 3 (2021): 250–256.
- "Randomized trial shows healthcare payment reform has equal-sized spillover effects on patients not targeted by reform," *PNAS* 117, no. 32 (2020): 18939–18947.
- "Bad Credit, No Problem? Credit and Labor Market Consequences of Bad Credit Reports." With Will Dobbie, Paul Goldsmith-Pinkham, and Jae Song. *Journal of Finance* 75, no. 3 (2020): 2377–2419.
- "How Do Americans Repay Their Debt? The Balance-Matching Heuristic." With John Gathergood, Neil Stewart, and Jörg Weber. *Economics Bulletin* 39, no. 2 (2019).
- "How Do Individuals Repay Their Debt? The Balance-Matching Heuristic." With John Gathergood, Neil Stewart, and Jörg Weber. *American Economic Review* 109, no. 3 (2019): 844–75
- "Externalities and Taxation of Supplemental Insurance: A Study of Medicare and Medigap." With Marika Cabral. *AEJ: Applied Economics* 11, no. 2 (2019): 37–73.
- "Provider Incentives and Health Care Costs: Evidence from Long-Term Care Hospitals." With Liran Einav and Amy Finkelstein. *Econometrica* 86, no. 6 (2018): 2161–2219.
- "Mandatory Medicare Bundled Payment Program for Lower Extremity Joint Replacement and Discharge to Institutional Postacute Care: Interim Analysis of the First Year of a 5-Year Randomized Trial." With Amy Finkelstein, Yunan Ji and Jonathan Skinner, *JAMA* 320, no. 9 (2018): 892–900.

- "Do Larger Health Insurance Subsidies Benefit Patients or Producers? Evidence from Medicare Advantage." With Marika Cabral and Michael Geruso. *American Economic Review* 108, no. 8 (2018): 2048–87.
- "Do Expiring Budgets Lead to Wasteful Year-End Spending? Evidence from Federal Procurement." With Jeffrey B. Liebman. *American Economic Review* 107, no. 11 (2017): 3510–3549.
- "Do Banks Pass-Through Credit Expansions to Consumers Who Want to Borrow?" With Sumit Agarwal, Souphala Chomsisengphet, and Johannes Stroebel. *Quarterly Journal of Economics* 133, no. 1 (2018): 129–190.
- "Imperfect Competition in Selection Markets." With E. Glen Weyl. *Review of Economics and Statistics* 99, no. 4 (2017): 637–651.
- "Regulating Consumer Financial Products: Evidence from Credit Cards." With Sumit Agarwal, Souphala Chomsisengphet, and Johannes Stroebel. *Quarterly Journal of Economics* 130, no. 1 (2015): 111–64.
- "Bankruptcy as Implicit Health Insurance." *American Economic Review* 105, no. 2 (2015): 710–46.
- "A Simple Framework for Estimating Consumer Benefits from Regulating Hidden Fees." With Sumit Agarwal, Souphala Chomsisengphet, and Johannes Stroebel. *Journal of Legal Studies* 43.S2 (2014): §§ 239–52.
- "Pricing and Welfare in Health Plan Choice." With M. Kate Bundorf and Jonathan Levin. *American Economic Review* 102, no. 7 (2012): 3214–48.

A.6.b. Other publications

- "What Does (Formal) Health Insurance Do, And for Whom? With Amy Finkelstein and Matthew J. Notowidigdo. *Annual Review of Economics* 10, no. 1 (2018): 261–286.
- "Competition Policy in Selection Markets." With Andre Veiga and E. Glen Weyl. *CPI Antitrust Chronicle* 2 (2014).
- "Messaging and the Mandate: The Impact of Consumer Experience on Health Insurance Enrollment through Exchanges." With Natalie Cox, Benjamin Handel, and Jonathan Kolstad. *American Economic Review Papers & Proceedings* 105, no. 5 (2015): 105–09.

A.6.c. Unpublished research papers

- "The Rise of Healthcare Jobs." With Joshua D Gottlieb, Kevin Rinz, and Victoria Udalova. NBER Working Paper 33583.

- "Producing Health: Measuring Value Added of Nursing Homes." With Liran Einav and Amy Finkelstein. Accepted, *Econometrica*.
- "Selling Subscriptions." With Liran Einav and Ben Klopack. Accepted *American Economic Review*.

A.6.d. Honors and awards

- ASHEcon Medal, 2021
- National Institutes of Health R01 "Health and Health Care Utilization Effects of Medical Debt Forgiveness," 2021
- J-PAL NA "Health and Health Care Utilization Effects of Medical Debt Forgiveness," 2019
- J-PAL NA "The Burden of Medical Debt and the Impact of Debt Forgiveness," 2017
- National Science Foundation Grant SES-1730466: "Empirical Studies of Financial Incentives in Publicly Provided Health Care," 2017
- Excellence in Refereeing Award, American Economic Review, 2017
- Sloan Research Fellowship, 2016
- Excellence in Refereeing Award, American Economic Review, 2015
- Excellence in Refereeing Award, American Economic Review, 2014
- Eric Zitzewitz Award, 2012
- National Tax Association Outstanding Doctoral Dissertation Award, First Runner-up, 2011
- Kapnick Fellowship, Stanford University, 2010–2011
- Outstanding Teaching Assistant Award, Stanford University, 2009
- Ric Weiland Graduate Fellowship (University-wide Award), Stanford University, 2008–2010
- Shultz Scholar, Stanford University, 2008–2009
- Graduate Fellowship, Stanford University 2005–2007
- Samuel C. Lamport Prize for the best undergraduate thesis in economics, Brown University, 2005
- Undergraduate Research Fellowship, Brown University, 2003

Appendix B. Materials Considered

(169) I incorporate by reference all materials cited in this expert report. Additional materials are cited below.

B.1. Expert reports and workpapers

- Expert Report of Craig Rosenberg, February 24, 2025.
- Expert Report of Donna L. Hoffman, February 24, 2025.
- Expert Report of James C. Cooper, February 24, 2025.
- Expert Report of Marshini Chetty, February 24, 2025.
- Expert Report of Ran Kivetz, February 24, 2025.
- Expert Report of Ronald T. Wilcox, February 24, 2025.
- Expert Report of William Violette, February 24, 2025.

B.2. Legal documents[153]

- Amended Complaint for Permanent Injunction, Civil Penalties, Monetary Relief, and Other Equitable Relief, *FTC v. Amazon.com, et al.*, No: 2:23-cv-00932-JHC (W.D. Wash. September 20, 2023), Dkt. #69.
- Amazon's Supplemental Objections & Responses to FTC's First Set of Interrogatories (April 10, 2024).
- Amazon's Second Supplemental Objections & Responses to FTC's First Set of Interrogatories (May 3, 2024).
- Amazon's letter regarding production of certain data (July 18, 2024).
- Amazon's letter regarding certain materials (December 6, 2024).
- Amazon's Written Objections & Responses to FTC's Notice of Rule 30(b)(6) Deposition of Amazon (February 13, 2025).

[153] All documents listed herein relate to the proceedings in *FTC v. Amazon.com, et al.*, No: 2:23-cv-00932-JHC (W.D. Wash.).

- Amazon's Supplemental Objections & Responses to FTC's Third Set of Interrogatories (March 21, 2025).

B.3. Bates numbered documents

- AMZN_00001500
- AMZN_00001517
- AMZN_00003642
- AMZN_00009360
- AMZN_00016867
- AMZN_00021537
- AMZN_00034290
- AMZN_00037413
- AMZN_00037417
- AMZN_00040674
- AMZN_00041335
- AMZN_00059329
- AMZN_00080322
- AMZN_00102785
- AMZN_00107862
- AMZN-PRM-FTC-000348598
- AMZN-PRM-FTC-000939073
- AMZN-PRM-FTC-001327233
- AMZN-PRM-FTC-002111339
- AMZN-PRM-FTC-002670757-758
- AMZN-PRM-FTC-002704614
- AMZN-PRM-FTC-002704619
- AMZN-PRM-FTC-002704620
- AMZN-PRM-FTC-002704624

- AMZN-PRM-FTC-002704632
- AMZN-PRM-FTC-002704651
- AMZN-PRM-FTC-002704653
- AMZN-PRM-FTC-002704655
- AMZN-PRM-FTC-002704657
- AMZN-PRM-FTC-002704669

B.4. Depositions, including exhibits and erratas

- Deposition of Benjamin Goeltz, October 30, 2024.
- Deposition of Benjamin Hills, January 17, 2025.
- Deposition of Caroline Abramowicz, November 7, 2024.
- Deposition of Emily Ikeda, February 20, 2025.

B.5. Data

- Exhibit A (To Letter Dated 2024.03.08).
- Exhibit A (To Letter Dated 2024.09.16) (Data Summary).
- Exhibit A (To Letter Dated 2024.10.25) (Supplemental Data Dictionary).
- Exhibit A (To Letter Dated 2024.11.07).
- Exhibit A (To Letter Dated 2024.12.06) (Data Summary).
- Exhibit A (To Letter Dated 2025.02.13) (Data Summary).
- 2024.03.08 Amazon Letter to FTC - Further Updated Data Sample.
- Benefits Usage (AMZN-PRM-FTC-DATA-00000009).
- Cancel Flow Data (AMZN-PRM-FTC-DATA-00000030).
- Cancel Survey Recipients (AMZN-PRM-FTC-DATA-00000016).
- Cancel Records (AMZN-PRM-FTC-DATA-00000007).
- Cancel Survey Data Qualtrics (AMZN-PRM-FTC-DATA-00000017).
- Cancel Survey Mapping v2 (AMZN-PRM-FTC-DATA-00000022).

- Chargebacks (AMZN-PRM-FTC-DATA-00000023).
- Period Plan (AMZN-PRM-FTC-DATA-00000001).
- Refunds (AMZN-PRM-FTC-DATA-00000020).
- Signup Location (AMZN-PRM-FTC-DATA-00000010).
- Transactions v2 (AMZN-PRM-FTC-DATA-00000019).

B.6. Publicly available documents and literature

B.6.a. Documents and websites

- "Amazon Prime," Amazon, https://www.amazon.com/amazonprime.
- "Amazon will increase the price of its annual Prime plan effective on May 11," Jillian D'Onfro, CNBC, https://www.cnbc.com/2018/04/26/amazon-will-increase-the-price-of-its-annual-prime-plan-effective-may-1.html.
- "Amazon increases the price of Prime nearly 17% to $139 per year," Annie Palmer, CNBC, https://www.cnbc.com/2022/02/03/amazon-increases-the-price-of-prime-nearly-17percent-to-139-per-year.html.
- "Prime Membership Benefits," Amazon, https://www.amazon.com/b/node=23945845011.
- "What Are the Differences Between the Amazon Music Subscriptions?," Amazon, https://www.amazon.com/gp/help/customer/display.html?nodeId=GW3PHAUCZM8L7W9L.
- "Free Shipping by Amazon," Amazon, https://www.amazon.com/gp/help/customer/display.html?nodeId=GZXW7X6AKTHNUP6H.

B.6.b. Academic literature

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Appendix C. Additional Survey questions

(170) In this appendix, I summarize responses to Questions 5 through 11 of the Cancellation Survey (responses to Questions 8 and 9 are not included because they call for text entries and responses vary widely).

Figure 39: Cancellation Survey responses for Question 5

Response	Question 5 *What are some reasons why you were making fewer purchases on Amazon?*
I did not trust the product quality	[redacted]
There were not enough items that were eligible for Prime shipping	
The merchandise prices were too high	
The items I wanted would not arrive in time	
I only needed to make purchases for certain holidays, occasions, or events	
Other (please specify)	
Blank (i.e., no response recorded)	
Total responses (including "Blank")	
Total responding subscribers	

Figure 40: Cancellation Survey responses for Question 6

Response	Question 6 *What are some reasons why you weren't using Prime benefits?*
I did not know of any benefits other than shipping	[redacted]
Amazon Fresh did not have enough selection or delivery times	
Amazon Music did not have enough songs that I like	
I was not using the game bonuses or channel subscription enough on Twitch Prime	
Prime Reading did not have enough books, magazines, or audible narrations that I like	
Prime Video did not have enough shows or movies that I want to watch	
Other (please specify)	
Blank (i.e., no response recorded)	
Total responses (including "Blank")	
Total responding subscribers	

Figure 41: Cancellation Survey responses for Question 7

Response	Question 7 *What problem(s) did you experience with Prime?*
I did not intend to sign up for Prime	[redacted]
Order arrived broken	
Deliveries were often stolen	
Deliveries were not made on time (after the date it was promised)	
Customer service was not able to resolve a problem with an order	
Prime membership fee was charged to the wrong credit card	
I needed deliveries to arrive sooner than the promised date shown	
Other (please specify)	
Blank (i.e., no response recorded)	
Total responses (including "Blank")	
Total responding subscribers	

Figure 42: Cancellation Survey responses for Question 10

Response	Question 10 *When are you most likely to rejoin Prime?*
Within the next month	[redacted]
Within the next 3 months	
Within the next 6 months	
Within the next 12 months	
Within the next 24 months	
Never	
Blank (i.e., no response recorded)	
Total responses (including "Blank")	
Total responding subscribers	

Figure 43: Cancellation Survey responses for Question 11

Response	Prime offers value	Prime rewards loyalty	Prime is designed for me	Prime makes life easier	Prime innovates
Completely disagree -1-	[redacted]				
-2-					
-3-					
-4-					
Completely agree -5-					
Blank (i.e., no response recorded)					
Total responses (including "Blank")					
Total responding subscribers					

(171) The next two figures summarize responses to Question 3 and Question 4, separately by signup method.

Figure 44: Proportion of responses to Question 3, by signup method

Signup method	Did not intend to sign up for Prime	Experienced a problem with Prime	Did not purchase enough for Prime	Did not use benefits enough	Too expensive	Other	Blank	Total responses
UPDP	[redacted]							
SOSP								
SPC								
Other signup methods								
All signup methods (combined)								

Figure 45: Proportion of responses to Question 4, by signup method

Signup method	Did not intend to sign up for Prime	Experienced a problem with Prime	Did not purchase enough for Prime	Did not use benefits enough	Too expensive	Other	No other reason	Blank	Total responses
UPDP	[redacted]								
SOSP									
SPC									
Other signup methods									
All signup methods (combined)									

Appendix D. Alternative methods to estimate unintended Prime subscription payments

D.1. Alternative method 1 (unintentional enrollment analysis)

(172) An intuitive and straightforward approach to estimate the total number of unintended enrollments is to apply the proportion of unintended enrollments in the Survey population for each enrollment channel to the population of Prime subscriptions for that enrollment channel and the payments made therein. Doing so, while limiting the subscriptions in the same manner as my baseline model, provides an alternative estimate of the number of unintentional enrollments and the harm.[154] This approach assumes that Survey respondents are similar to and reflective of the total population of Prime subscribers for each enrollment channel. Under this method, for signups on or after January 1, 2018 and payments made on or after a cutoff date of December 29, 2018, I estimate a total of [redacted] unintentional enrollments and $939 million of harm for the signup methods at issue. The figures below show these values along with analogous estimates for various alternative samples of subscriptions and associated payments, based on payment date and subscription start date respectively.

[154] *See* Section III.B for a description of the limitations I apply to the subscriptions that I include in these calculations.

Figure 46: Alternative method 1 harm estimates, for cutoff dates applied to payments

Signup method	Cutoff date	Share of unintentional enrollments	Count of unintentional enrollments (M)	Harm from unintentional enrollments ($M)
SOSP	6/21/2018	[redacted]		
SPC	6/21/2018			
UPDP	6/21/2018			
TOTAL	**6/21/2018**			
SOSP	12/29/2018			
SPC	12/29/2018			
UPDP	12/29/2018			
TOTAL	**12/29/2018**			
SOSP	7/20/2019			
SPC	7/20/2019			
UPDP	7/20/2019			
TOTAL	**7/20/2019**			
SOSP	1/19/2020			
SPC	1/19/2020			
UPDP	1/19/2020			
TOTAL	**1/19/2020**			
SOSP	6/21/2020			
SPC	6/21/2020			
UPDP	6/21/2020			
TOTAL	**6/21/2020**			
SOSP	9/20/2020			
SPC	9/20/2020			
UPDP	9/20/2020			
TOTAL	**9/20/2020**			

Figure 47: Alternative method 1 harm estimates, for cutoff dates applied to subscription start dates

Signup method	Cutoff date	Share of unintentional enrollments	Count of unintentional enrollments (M)	Harm from unintentional enrollments ($M)
SOSP	6/21/2018	[redacted]	[redacted]	[redacted]
SPC	6/21/2018	[redacted]	[redacted]	[redacted]
UPDP	6/21/2018	[redacted]	[redacted]	[redacted]
TOTAL	**6/21/2018**	[redacted]	[redacted]	[redacted]
SOSP	12/29/2018	[redacted]	[redacted]	[redacted]
SPC	12/29/2018	[redacted]	[redacted]	[redacted]
UPDP	12/29/2018	[redacted]	[redacted]	[redacted]
TOTAL	**12/29/2018**	[redacted]	[redacted]	[redacted]
SOSP	7/20/2019	[redacted]	[redacted]	[redacted]
SPC	7/20/2019	[redacted]	[redacted]	[redacted]
UPDP	7/20/2019	[redacted]	[redacted]	[redacted]
TOTAL	**7/20/2019**	[redacted]	[redacted]	[redacted]
SOSP	1/19/2020	[redacted]	[redacted]	[redacted]
SPC	1/19/2020	[redacted]	[redacted]	[redacted]
UPDP	1/19/2020	[redacted]	[redacted]	[redacted]
TOTAL	**1/19/2020**	[redacted]	[redacted]	[redacted]
SOSP	6/21/2020	[redacted]	[redacted]	[redacted]
SPC	6/21/2020	[redacted]	[redacted]	[redacted]
UPDP	6/21/2020	[redacted]	[redacted]	[redacted]
TOTAL	**6/21/2020**	[redacted]	[redacted]	[redacted]
SOSP	9/20/2020	[redacted]	[redacted]	[redacted]
SPC	9/20/2020	[redacted]	[redacted]	[redacted]
UPDP	9/20/2020	[redacted]	[redacted]	[redacted]
TOTAL	**9/20/2020**	[redacted]	[redacted]	[redacted]

D.2. Alternative method 2 (unintentional enrollment analysis)

(173) My next approach to estimate the extent of unintentional enrollment is a more flexible version of Alternative method 1 that matches Survey respondents who identify as unintentional enrollees to the broader population of Prime subscribers at a more granular level. Specifically, in addition to matching based on signup method, I also match members of the population to Cancellation Survey respondents based on Prime subscription length and usage of Prime shipping benefits. As I show in Section III.A, benefits usage is correlated with Survey responses and matching on this characteristic allows for better predictions of unintentional enrollment.

(174) Figure 48 and Figure 49 below show that Survey respondents and the random sample of the Prime population have similar distributions of subscription length. Survey respondents tend to have somewhat higher Prime shipping benefit usage but nonetheless overlap substantially with the population.

Figure 48: Distribution of subscription length

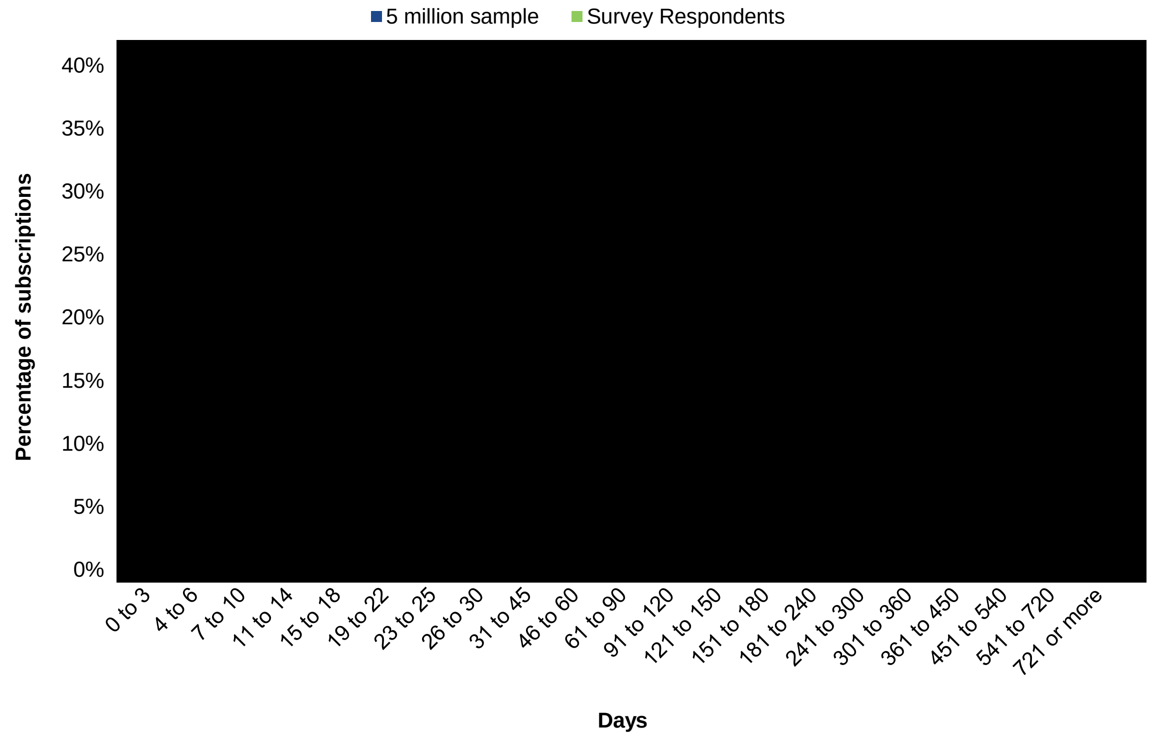
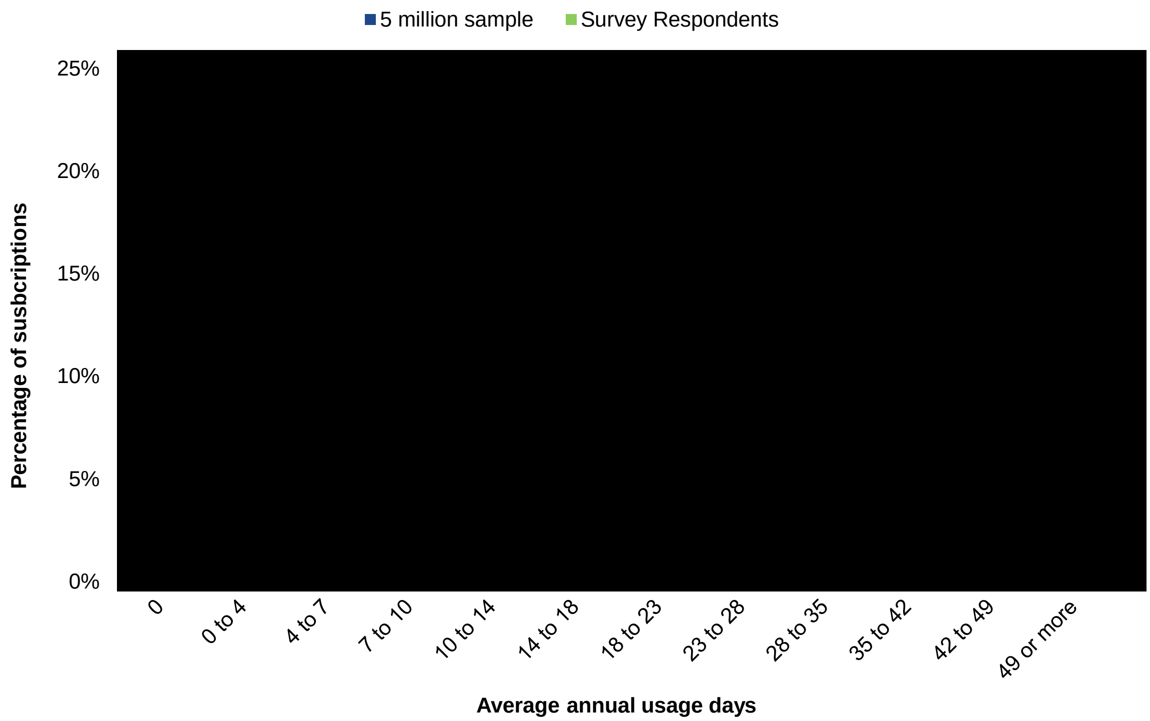


Figure 49: Distribution of Prime shipping benefit use



(175) In this refinement, I estimate rates of unintentional enrollment among the Prime population based on the responses of Cancellation Survey respondents who are similar to them. This will allow for better prediction of rates of unintentional enrollment because, as shown in Figure 24, Prime shipping benefit usage is correlated with Survey responses (and, specifically, with "did not intend" responses). I implement the methodology, separately for subscriptions initiated through each signup method and limited in the same manner as my baseline method:

1. Split the population of Survey respondents into 16 groups defined by the full interaction of quartiles of membership duration and quartiles of Prime shipping benefit usage for each enrollment channel.[155]
2. Calculate, separately for each of these 16 groups, the percentage of subscriptions for which the customer indicated no intent to sign up for Prime.
3. Divide a random sample of the broader population into the corresponding 16 groups based on quartiles of membership duration and shipping benefit usage, limiting to subscriptions that cancelled at some point in time. Apply the group-specific proportions from the second step to estimate the number of unintentional signups in the overall population.

[155] *See* Section III.B for a description of the limitations I apply to the subscriptions that I include in these calculations.

(176) Under this method, for signups on or after January 1, 2018 and payments made on or after a cutoff date of December 29, 2018, I estimate a total of [redacted] unintentional enrollments and $842 million in harm for the signup methods at issue. In addition, Figure 50 and Figure 51 includes estimates for various alternative groups of subscriptions and associated payments based on the payment dates and subscription start dates.

Figure 50: Alternative method 2 harm estimates, for cutoff dates applied to payments

Signup method	Cutoff date	Share of unintentional enrollments	Count of unintentional enrollments (M)	Harm from unintentional enrollments ($M)
SOSP	6/21/2018	[redacted]	[redacted]	[redacted]
SPC	6/21/2018	[redacted]	[redacted]	[redacted]
UPDP	6/21/2018	[redacted]	[redacted]	[redacted]
TOTAL	**6/21/2018**	[redacted]	[redacted]	[redacted]
SOSP	12/29/2018	[redacted]	[redacted]	[redacted]
SPC	12/29/2018	[redacted]	[redacted]	[redacted]
UPDP	12/29/2018	[redacted]	[redacted]	[redacted]
TOTAL	**12/29/2018**	[redacted]	[redacted]	[redacted]
SOSP	7/20/2019	[redacted]	[redacted]	[redacted]
SPC	7/20/2019	[redacted]	[redacted]	[redacted]
UPDP	7/20/2019	[redacted]	[redacted]	[redacted]
TOTAL	**7/20/2019**	[redacted]	[redacted]	[redacted]
SOSP	1/19/2020	[redacted]	[redacted]	[redacted]
SPC	1/19/2020	[redacted]	[redacted]	[redacted]
UPDP	1/19/2020	[redacted]	[redacted]	[redacted]
TOTAL	**1/19/2020**	[redacted]	[redacted]	[redacted]
SOSP	6/21/2020	[redacted]	[redacted]	[redacted]
SPC	6/21/2020	[redacted]	[redacted]	[redacted]
UPDP	6/21/2020	[redacted]	[redacted]	[redacted]
TOTAL	**6/21/2020**	[redacted]	[redacted]	[redacted]
SOSP	9/20/2020	[redacted]	[redacted]	[redacted]
SPC	9/20/2020	[redacted]	[redacted]	[redacted]
UPDP	9/20/2020	[redacted]	[redacted]	[redacted]
TOTAL	**9/20/2020**	[redacted]	[redacted]	[redacted]

Figure 51: Alternative method 2 harm estimates, for cutoff dates applied to subscription start dates

Signup method	Cutoff date	Share of unintentional enrollments	Count of unintentional enrollments (M)	Harm from unintentional enrollments ($M)
SOSP	6/21/2018	[redacted]		
SPC	6/21/2018			
UPDP	6/21/2018			
TOTAL	**6/21/2018**			
SOSP	12/29/2018			
SPC	12/29/2018			
UPDP	12/29/2018			
TOTAL	**12/29/2018**			
SOSP	7/20/2019			
SPC	7/20/2019			
UPDP	7/20/2019			
TOTAL	**7/20/2019**			
SOSP	1/19/2020			
SPC	1/19/2020			
UPDP	1/19/2020			
TOTAL	**1/19/2020**			
SOSP	6/21/2020			
SPC	6/21/2020			
UPDP	6/21/2020			
TOTAL	**6/21/2020**			
SOSP	9/20/2020			
SPC	9/20/2020			
UPDP	9/20/2020			
TOTAL	**9/20/2020**			

D.3. Baseline model predictions (unintentional enrollment analysis)

(177) The figures below display how the predicted proportion of harmed subscriptions varies with the characteristics used in the predictive model; namely, the average usage of Prime shipping benefits during a year, the average usage of non-shipping Prime benefits during a year, and the length of a subscription. Specifically, the figures show the mean predicted harm for subscriptions when they are divided into two groups based on whether a given characteristic is above or below the corresponding median value. The figures show that, across the three enrollment channels, the predicted proportion of harmed subscriptions is higher among customers with lower usage and shorter subscriptions.

Figure 52: Predicted proportion of harmed subscriptions, for subscriptions with above- versus below-median Prime shipping benefits usage per year

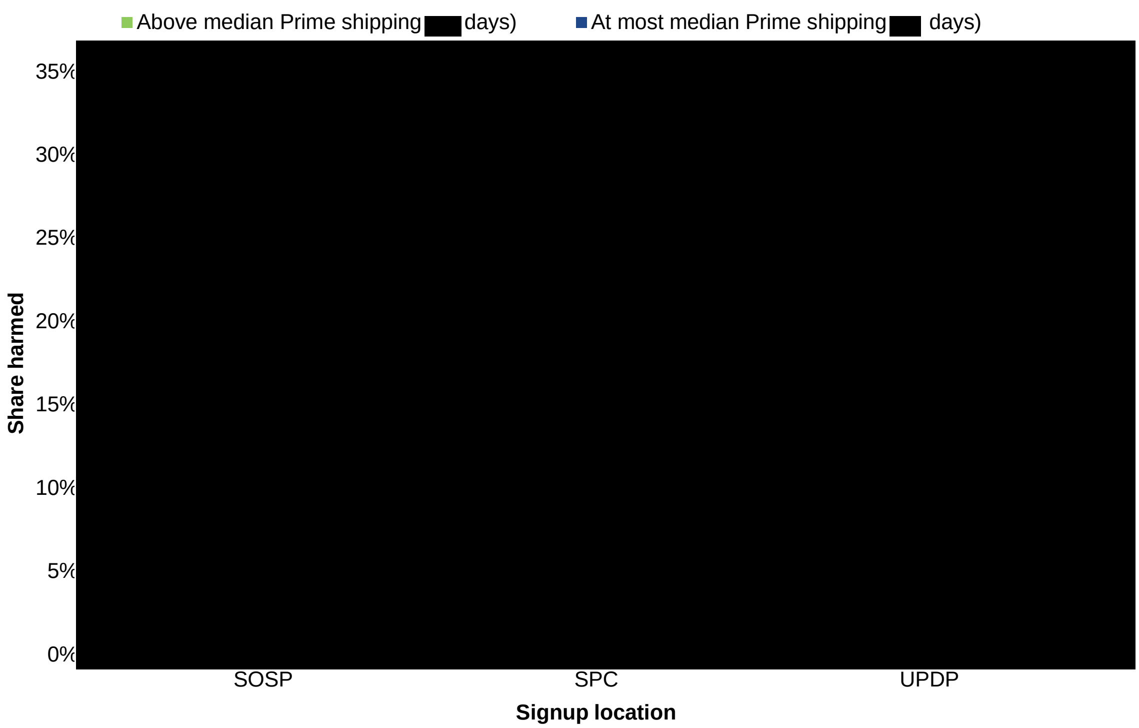


Figure 53: Predicted proportion of harmed subscriptions, for subscriptions with above- versus below-median Prime non-shipping benefits usage per year

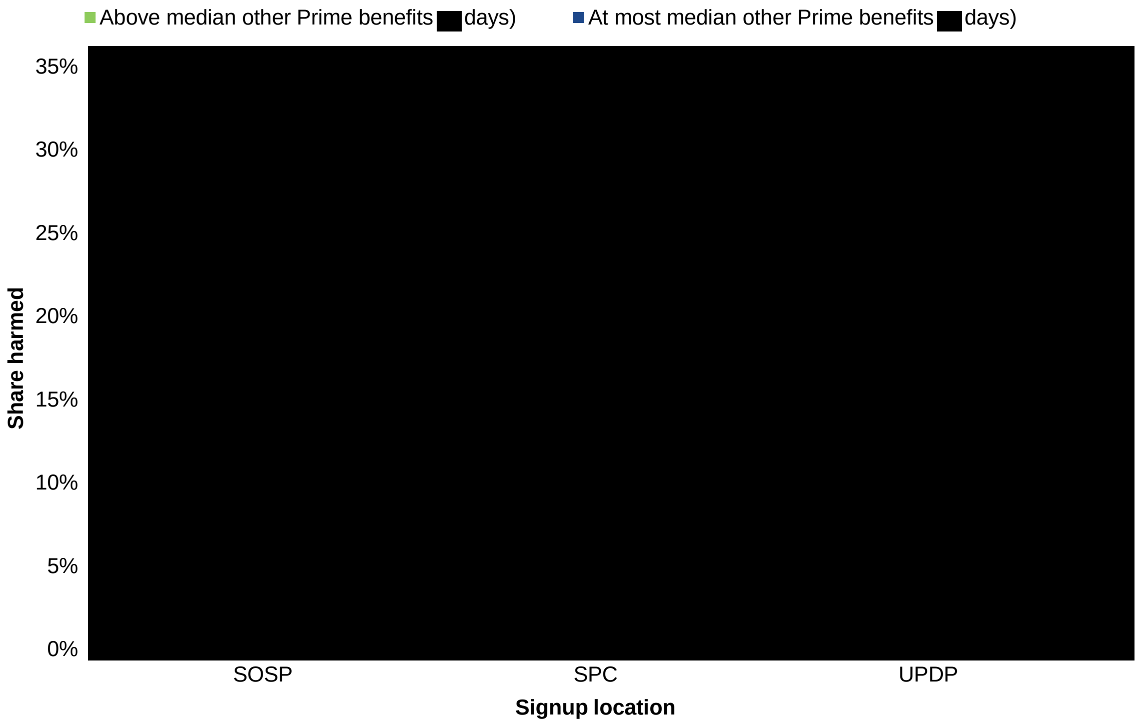
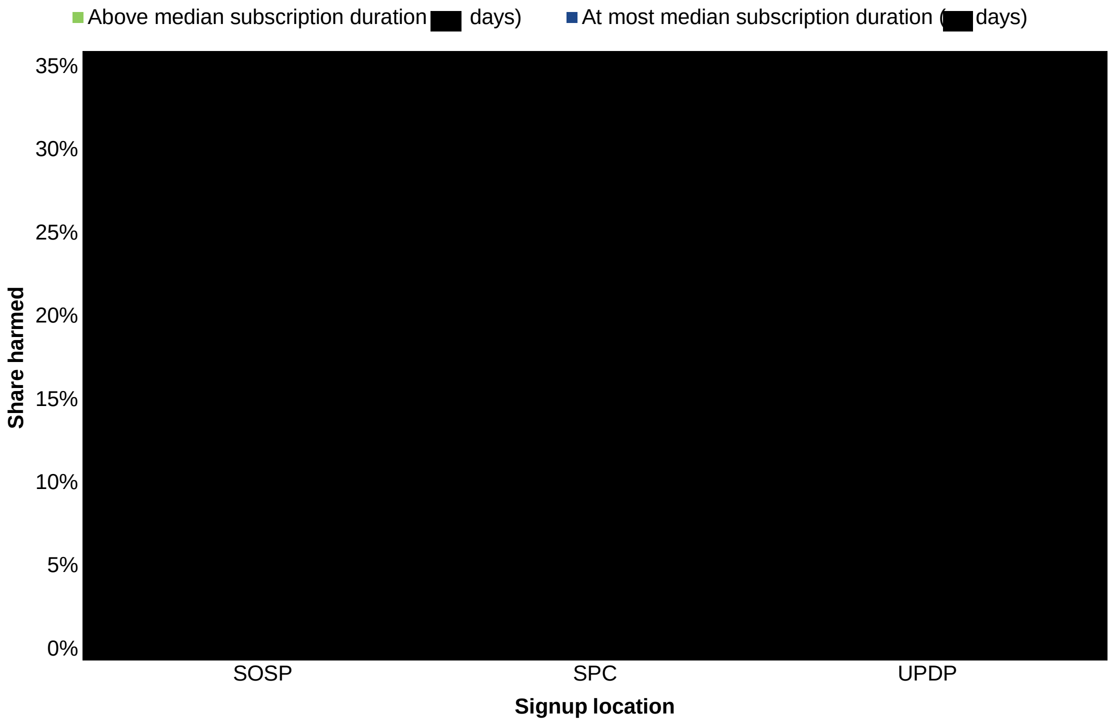


Figure 54: Predicted proportion of harmed subscriptions, for subscriptions with above- versus below-median subscription length



D.4. Baseline method sensitivities and variations

D.4.a. Sensitivities for alternative time periods

(178) Figure 55 and Figure 56 show estimates of harm using my baseline method limited to alternative time periods based on the start date for counting payments or subscriptions. As with my baseline estimates, I also limit these estimates to subscriptions that were (1) were cancelled before June 21, 2023 (as is also the case for Cancellation Survey respondents' subscriptions), (2) consisted wholly or partly of monthly plans, and (3) were initiated via the UPDP, SOSP, and SPC signup methods.[156] Further, the estimate of excess payments that were made as a result of unintentional enrollments is additionally limited to (1) payments for monthly plans and (2) payments that were made on or before a subscriber first entered a cancellation process (even if they did not successfully cancel).[157]

[156] *See* Section III.B.

[157] *See* Section III.B.

(179) Figure 57 and Figure 58 show additional sensitivities in which I estimate the rate of harm only among subscriptions that were cancelled after the Cancellation Survey was initiated, so as to apply the Survey only to Prime subscribers who cancelled contemporaneously. I retain the restrictions described above.

Figure 55: Baseline method harm estimates, for subscriptions initiated on or after January 1, 2018, and payments after cutoff date

Signup method	Cutoff date	Share of unintentional enrollments	Count of unintentional enrollments (M)	Harm from unintentional enrollments ($M)
SOSP	6/21/2018	[redacted]		
SPC	6/21/2018	[redacted]		
UPDP	6/21/2018	[redacted]		
TOTAL	**6/21/2018**	[redacted]		
SOSP	7/20/2019	[redacted]		
SPC	7/20/2019	[redacted]		
UPDP	7/20/2019	[redacted]		
TOTAL	**7/20/2019**	[redacted]		
SOSP	1/19/2020	[redacted]		
SPC	1/19/2020	[redacted]		
UPDP	1/19/2020	[redacted]		
TOTAL	**1/19/2020**	[redacted]		
SOSP	6/21/2020	[redacted]		
SPC	6/21/2020	[redacted]		
UPDP	6/21/2020	[redacted]		
TOTAL	**6/21/2020**	[redacted]		
SOSP	9/20/2020	[redacted]		
SPC	9/20/2020	[redacted]		
UPDP	9/20/2020	[redacted]		
TOTAL	**9/20/2020**	[redacted]		

Note: Results for the cutoff date of 12/29/2018 may be found in the main text.

Figure 56: Baseline method harm estimates, for subscriptions initiated on or after cutoff date

Signup method	Cutoff date	Share of unintentional enrollments	Count of unintentional enrollments (M)	Harm from unintentional enrollments ($M)
SOSP	6/21/2018	[redacted]		
SPC	6/21/2018			
UPDP	6/21/2018			
TOTAL	**6/21/2018**			
SOSP	12/29/2018			
SPC	12/29/2018			
UPDP	12/29/2018			
TOTAL	**12/29/2018**			
SOSP	7/20/2019			
SPC	7/20/2019			
UPDP	7/20/2019			
TOTAL	**7/20/2019**			
SOSP	1/19/2020			
SPC	1/19/2020			
UPDP	1/19/2020			
TOTAL	**1/19/2020**			
SOSP	6/21/2020			
SPC	6/21/2020			
UPDP	6/21/2020			
TOTAL	**6/21/2020**			
SOSP	9/20/2020			
SPC	9/20/2020			
UPDP	9/20/2020			
TOTAL	**9/20/2020**			

Figure 57: Baseline method harm estimates, restricted to subscriptions that were cancelled after the Cancellation Survey was initiated (May 2020), for subscriptions initiated on or after January 1, 2018, and payments after cutoff date

Signup method	Cutoff date	Share of unintentional enrollments
SOSP	6/21/2018	[redacted]
SPC	6/21/2018	
UPDP	6/21/2018	
TOTAL	**6/21/2018**	
SOSP	12/29/2018	
SPC	12/29/2018	
UPDP	12/29/2018	
TOTAL	**12/29/2018**	
SOSP	7/20/2019	
SPC	7/20/2019	
UPDP	7/20/2019	
TOTAL	**7/20/2019**	
SOSP	1/19/2020	
SPC	1/19/2020	
UPDP	1/19/2020	
TOTAL	**1/19/2020**	
SOSP	6/21/2020	
SPC	6/21/2020	
UPDP	6/21/2020	
TOTAL	**6/21/2020**	
SOSP	9/20/2020	
SPC	9/20/2020	
UPDP	9/20/2020	
TOTAL	**9/20/2020**	

Figure 58: Baseline method harm estimates, restricted to subscriptions that were cancelled after the Cancellation Survey was initiated (May 2020), for subscriptions initiated on or after cutoff date

Signup method	Cutoff date	Share of unintentional enrollments
SOSP	6/21/2018	[redacted]
SPC	6/21/2018	
UPDP	6/21/2018	
TOTAL	**6/21/2018**	
SOSP	12/29/2018	
SPC	12/29/2018	
UPDP	12/29/2018	
TOTAL	**12/29/2018**	
SOSP	7/20/2019	
SPC	7/20/2019	
UPDP	7/20/2019	
TOTAL	**7/20/2019**	
SOSP	1/19/2020	
SPC	1/19/2020	
UPDP	1/19/2020	
TOTAL	**1/19/2020**	
SOSP	6/21/2020	
SPC	6/21/2020	
UPDP	6/21/2020	
TOTAL	**6/21/2020**	
SOSP	9/20/2020	
SPC	9/20/2020	
UPDP	9/20/2020	
TOTAL	**9/20/2020**	

D.4.b. Alternative implementation using logistic regression

(180) Figure 59 and Figure 60 show the rate of unintentional enrollment predicted by the baseline method implemented using a logistic regression (i.e., a logit model). The values shown for a cutoff date of December 29, 2018 in Figure 59 apply the same limitations as my baseline estimate in Figure 25. For other values, Figure 59 uses subscriptions and payments subject to the same limitations as Figure 55, while Figure 60 parallels the limitations used in Figure 56.

Figure 59: Baseline method implemented using a Logistic regression, for subscriptions initiated on or after January 1, 2018, and payments after cutoff date

Signup method	Cutoff date	Share of unintentional enrollments
SOSP	6/21/2018	[redacted]
SPC	6/21/2018	
UPDP	6/21/2018	
TOTAL	**6/21/2018**	
SOSP	12/29/2018	
SPC	12/29/2018	
UPDP	12/29/2018	
TOTAL	**12/29/2018**	
SOSP	7/20/2019	
SPC	7/20/2019	
UPDP	7/20/2019	
TOTAL	**7/20/2019**	
SOSP	1/19/2020	
SPC	1/19/2020	
UPDP	1/19/2020	
TOTAL	**1/19/2020**	
SOSP	6/21/2020	
SPC	6/21/2020	
UPDP	6/21/2020	
TOTAL	**6/21/2020**	
SOSP	9/20/2020	
SPC	9/20/2020	
UPDP	9/20/2020	
TOTAL	**9/20/2020**	

Figure 60: Baseline method implemented using a logistic regression, for subscriptions initiated on or after cutoff date

Signup method	Cutoff date	Share of unintentional enrollments
SOSP	6/21/2018	[redacted]
SPC	6/21/2018	
UPDP	6/21/2018	
TOTAL	**6/21/2018**	
SOSP	12/29/2018	
SPC	12/29/2018	
UPDP	12/29/2018	
TOTAL	**12/29/2018**	
SOSP	7/20/2019	
SPC	7/20/2019	
UPDP	7/20/2019	
TOTAL	**7/20/2019**	
SOSP	1/19/2020	
SPC	1/19/2020	
UPDP	1/19/2020	
TOTAL	**1/19/2020**	
SOSP	6/21/2020	
SPC	6/21/2020	
UPDP	6/21/2020	
TOTAL	**6/21/2020**	
SOSP	9/20/2020	
SPC	9/20/2020	
UPDP	9/20/2020	
TOTAL	**9/20/2020**	

D.4.c. Extension of estimated harm from baseline method to September 2025

(181) For each set of cutoff dates, and signup methods, I extrapolate estimated harm from the baseline method to September 2025 as follows.

1. Limit to subscriptions that (1) began on or after January 1, 2018, (2) were cancelled before June 21, 2023, (3) consisted wholly or partly of monthly plans, and (4) were initiated via the UPDP, SOSP, and SPC signup methods. Estimate the baseline model.

2. Calculate the predicted payments associated with (1) unintentional enrollments for monthly plans, (2) payments that were made on or before a subscriber first entered a cancellation process (even if they did not successfully cancel), and (3) each pair of signup method and cutoff date.
3. Estimate the total predicted harm by month of subscription cancellation for the last 12 consecutive full months (June 2022–May 2023) in the data. Average this estimate to obtain an average predicted harm per month, for each pair of signup method and cutoff date.
4. Extrapolate this estimate of average harm per month from June 21, 2023, to September 30, 2025.

The figures below show the extrapolated estimates for various time periods based on the start date for counting payments or subscriptions.

Figure 61: Harm estimates from baseline method, extrapolated to September 2025, for subscriptions initiated on or after January 1, 2018, and payments after cutoff date

Signup method	Cutoff date	Unintentional enrollment harm until June 21, 2023 ($M)	Additional unintentional enrollment harm, June 21, 2023 to September 30, 2025 ($M)	Total harm from unintentional enrollments
SOSP	6/21/2018	[redacted]	[redacted]	[redacted]
SPC	6/21/2018	[redacted]	[redacted]	[redacted]
UPDP	6/21/2018	[redacted]	[redacted]	[redacted]
TOTAL	**6/21/2018**	[redacted]	[redacted]	[redacted]
SOSP	12/29/2018	[redacted]	[redacted]	[redacted]
SPC	12/29/2018	[redacted]	[redacted]	[redacted]
UPDP	12/29/2018	[redacted]	[redacted]	[redacted]
TOTAL	**12/29/2018**	[redacted]	[redacted]	[redacted]
SOSP	7/20/2019	[redacted]	[redacted]	[redacted]
SPC	7/20/2019	[redacted]	[redacted]	[redacted]
UPDP	7/20/2019	[redacted]	[redacted]	[redacted]
TOTAL	**7/20/2019**	[redacted]	[redacted]	[redacted]
SOSP	1/19/2020	[redacted]	[redacted]	[redacted]
SPC	1/19/2020	[redacted]	[redacted]	[redacted]
UPDP	1/19/2020	[redacted]	[redacted]	[redacted]
TOTAL	**1/19/2020**	[redacted]	[redacted]	[redacted]
SOSP	6/21/2020	[redacted]	[redacted]	[redacted]
SPC	6/21/2020	[redacted]	[redacted]	[redacted]
UPDP	6/21/2020	[redacted]	[redacted]	[redacted]
TOTAL	**6/21/2020**	[redacted]	[redacted]	[redacted]
SOSP	9/20/2020	[redacted]	[redacted]	[redacted]
SPC	9/20/2020	[redacted]	[redacted]	[redacted]
UPDP	9/20/2020	[redacted]	[redacted]	[redacted]
TOTAL	**9/20/2020**	[redacted]	[redacted]	[redacted]

Figure 62: Harm estimates from baseline method, extrapolated to September 2025, for subscriptions initiated on or after cutoff date

Signup method	Date cutoff	Unintentional enrollment harm until June 21, 2023 ($M)	Additional unintentional enrollment harm, June 21, 2023 to September 30, 2025 ($M)	Total harm from unintentional enrollments
SOSP	6/21/2018	[redacted]		
SPC	6/21/2018			
UPDP	6/21/2018			
TOTAL	**6/21/2018**			
SOSP	12/29/2018			
SPC	12/29/2018			
UPDP	12/29/2018			
TOTAL	**12/29/2018**			
SOSP	7/20/2019			
SPC	7/20/2019			
UPDP	7/20/2019			
TOTAL	**7/20/2019**			
SOSP	1/19/2020			
SPC	1/19/2020			
UPDP	1/19/2020			
TOTAL	**1/19/2020**			
SOSP	6/21/2020			
SPC	6/21/2020			
UPDP	6/21/2020			
TOTAL	**6/21/2020**			
SOSP	9/20/2020			
SPC	9/20/2020			
UPDP	9/20/2020			
TOTAL	**9/20/2020**			

Appendix E. Additional figures related to incomplete cancellations

E.1. DID estimates without excluding the 5-day window around the date of cancellation process entry

Figure 63: Difference-in-differences estimates of the increase in zero benefit usage for the No Page and Prime Central action groups, usage window restricted to 90 days pre- and post-entry and with the five days before and after entry included

Treatment group	Coefficient
No Page	[redacted]
Prime Central	

Note. Results are based on usage in up to 90-day windows around the date of cancellation process entry, with the 5 days pre- and post-entry included.

E.2. Additional harm estimates

Figure 64: Harm estimates for unsuccessful cancellers, by action group

Action group	Additional Prime fee payments after unsuccessful cancellation ($M)
No Page	[redacted]
Prime Central	

Note. Results are based on usage in up to 90-day windows around the date of cancellation process entry, with the 5 days pre- and post-entry excluded. Limited to both entry and payments made after December 29, 2018. Excludes Prime fees after subsequent cancellation process entry.

Figure 65: Harm estimates for unsuccessful cancellers, by action group and cutoff dates

Cutoff date	Action group	Limited to payment date after cutoff date ($M)	Limited to payment date and cancellation entry date after cutoff date ($M)
7/20/2019	No Page	[redacted]	
	Prime Central		
1/19/2020	No Page		
	Prime Central		
6/21/2020	No Page		
	Prime Central		
9/20/2020	No Page		
	Prime Central		

Note. Results are based on usage in up to 90-day windows around the date of cancellation process entry (excluding the 5 days around the entry date). Excludes Prime fees after subsequent cancellation process entry.

E.3. Attempted cancellers

Figure 66: Subscriptions and post-entry Prime payments among subscribers who enter the cancellation process but do not cancel, by action group (limited to fees paid after July 20, 2019)

Scenario	Action group	Count of subscriptions (M)	Prime monthly fee payments post-cancellation process entry ($M)
1. Cancellation process entries	No Page	[redacted]	
	Prime Central		
	KMB/KMM		
	Remind Me Later		
	Other		
2. Cancellation process entries with flat or decreased subsequent Prime benefits usage	No Page		
	Prime Central		
	KMB/KMM		
	Remind Me Later		
	Other		
3. D-I-D estimates (vs. Accept an Offer)	No Page		
	Prime Central		
	KMB/KMM		
	Remind Me Later		
	Other		

Note. Based on comparing usage in the 90-day window around cancellation entry (excluding the 5 days around the entry date).

Figure 67: Subscriptions and post-entry Prime payments among subscribers who enter the cancellation process but do not cancel, by action group (limited to fees paid after January 19, 2020)

Scenario	Action group	Count of subscriptions (M)	Prime monthly fee payments post-cancellation process entry ($M)
1. Cancellation process entries	No Page	[redacted]	[redacted]
	Prime Central	[redacted]	[redacted]
	KMB/KMM	[redacted]	[redacted]
	Remind Me Later	[redacted]	[redacted]
	Other	[redacted]	[redacted]
2. Cancellation process entries with flat or decreased subsequent Prime benefits usage	No Page	[redacted]	[redacted]
	Prime Central	[redacted]	[redacted]
	KMB/KMM	[redacted]	[redacted]
	Remind Me Later	[redacted]	[redacted]
	Other	[redacted]	[redacted]
3. D-I-D estimates (vs. Accept an Offer)	No Page	[redacted]	[redacted]
	Prime Central	[redacted]	[redacted]
	KMB/KMM	[redacted]	[redacted]
	Remind Me Later	[redacted]	[redacted]
	Other	[redacted]	[redacted]

Note. Based on comparing usage in the 90-day window around cancellation entry (excluding the 5 days around the entry date).

Figure 68: Subscriptions and post-entry Prime payments among subscribers who enter the cancellation process but do not cancel, by action group (limited to fees paid after June 21, 2020)

Scenario	Action group	Count of subscriptions (M)	Prime monthly fee payments post-cancellation process entry ($M)
1. Cancellation process entries	No Page	[redacted]	[redacted]
	Prime Central	[redacted]	[redacted]
	KMB/KMM	[redacted]	[redacted]
	Remind Me Later	[redacted]	[redacted]
	Other	[redacted]	[redacted]
2. Cancellation process entries with flat or decreased subsequent Prime benefits usage	No Page	[redacted]	[redacted]
	Prime Central	[redacted]	[redacted]
	KMB/KMM	[redacted]	[redacted]
	Remind Me Later	[redacted]	[redacted]
	Other	[redacted]	[redacted]
3. D-I-D estimates (vs. Accept an Offer)	No Page	[redacted]	[redacted]
	Prime Central	[redacted]	[redacted]
	KMB/KMM	[redacted]	[redacted]
	Remind Me Later	[redacted]	[redacted]
	Other	[redacted]	[redacted]

Note. Based on comparing usage in the 90-day window around cancellation entry (excluding the 5 days around the entry date).

Figure 69: Subscriptions and post-entry Prime payments among subscribers who enter the cancellation process but do not cancel, by action group (limited to fees paid after September 20, 2020)

Scenario	Action group	Count of subscriptions (M)	Prime monthly fee payments post-cancellation process entry ($M)
1. Cancellation process entries	No Page	[redacted]	
	Prime Central		
	KMB/KMM		
	Remind Me Later		
	Other		
2. Cancellation process entries with flat or decreased subsequent Prime benefits usage	No Page		
	Prime Central		
	KMB/KMM		
	Remind Me Later		
	Other		
3. D-I-D estimates (vs. Accept an Offer)	No Page		
	Prime Central		
	KMB/KMM		
	Remind Me Later		
	Other		

Note. Based on comparing usage in the 90-day window around cancellation entry (excluding the 5 days around the entry date).

Figure 70: Subscriptions and post-entry Prime payments among subscribers who enter the cancellation process but do not cancel, by action group (limited to cancellation entry and fees paid after December 29, 2018)

Scenario	Action group	Count of subscriptions (M)	Prime monthly fee payments post-cancellation process entry ($M)
1. Cancellation process entries	No Page	[redacted]	
	Prime Central		
	KMB/KMM		
	Remind Me Later		
	Other		
2. Cancellation process entries with flat or decreased subsequent Prime benefits usage	No Page		
	Prime Central		
	KMB/KMM		
	Remind Me Later		
	Other		
3. D-I-D estimates (vs. Accept an Offer)	No Page		
	Prime Central		
	KMB/KMM		
	Remind Me Later		
	Other		

Note. Based on comparing usage in the 90-day window around cancellation entry (excluding the 5 days around the entry date).

Figure 71: Subscriptions and post-entry Prime payments among subscribers who enter the cancellation process but do not cancel, by action group (limited to cancellation entry and fees paid after July 20, 2019)

Scenario	Action group	Count of subscriptions (M)	Prime monthly fee payments post-cancellation process entry ($M)
1. Cancellation process entries	No Page	[redacted]	
	Prime Central		
	KMB/KMM		
	Remind Me Later		
	Other		
2. Cancellation process entries with flat or decreased subsequent Prime benefits usage	No Page		
	Prime Central		
	KMB/KMM		
	Remind Me Later		
	Other		
3. D-I-D estimates (vs. Accept an Offer)	No Page		
	Prime Central		
	KMB/KMM		
	Remind Me Later		
	Other		

Note. Based on comparing usage in the 90-day window around cancellation entry (excluding the 5 days around the entry date).

Figure 72: Subscriptions and post-entry Prime payments among subscribers who enter the cancellation process but do not cancel, by action group (limited to cancellation entry and fees paid after January 19, 2020)

Scenario	Action group	Count of subscriptions (M)	Prime monthly fee payments post-cancellation process entry ($M)
1. Cancellation process entries	No Page	[redacted]	
	Prime Central		
	KMB/KMM		
	Remind Me Later		
	Other		
2. Cancellation process entries with flat or decreased subsequent Prime benefits usage	No Page		
	Prime Central		
	KMB/KMM		
	Remind Me Later		
	Other		
3. D-I-D estimates (vs. Accept an Offer)	No Page		
	Prime Central		
	KMB/KMM		
	Remind Me Later		
	Other		

Note. Based on comparing usage in the 90-day window around cancellation entry (excluding the 5 days around the entry date).

Figure 73: Subscriptions and post-entry Prime payments among subscribers who enter the cancellation process but do not cancel, by action group (limited to cancellation entry and fees paid after June 21, 2020)

Scenario	Action group	Count of subscriptions (M)	Prime monthly fee payments post-cancellation process entry ($M)
1. Cancellation process entries	No Page	[redacted]	[redacted]
	Prime Central		
	KMB/KMM		
	Remind Me Later		
	Other		
2. Cancellation process entries with flat or decreased subsequent Prime benefits usage	No Page		
	Prime Central		
	KMB/KMM		
	Remind Me Later		
	Other		
3. D-I-D estimates (vs. Accept an Offer)	No Page		
	Prime Central		
	KMB/KMM		
	Remind Me Later		
	Other		

Note. Based on comparing usage in the 90-day window around cancellation entry (excluding the 5 days around the entry date).

Figure 74: Subscriptions and post-entry Prime payments among subscribers who enter the cancellation process but do not cancel, by action group (limited to cancellation entry and fees paid after September 20, 2020)

Scenario	Action group	Count of subscriptions (M)	Prime monthly fee payments post-cancellation process entry ($M)
1. Cancellation process entries	No Page	[redacted]	[redacted]
	Prime Central		
	KMB/KMM		
	Remind Me Later		
	Other		
2. Cancellation process entries with flat or decreased subsequent Prime benefits usage	No Page		
	Prime Central		
	KMB/KMM		
	Remind Me Later		
	Other		
3. D-I-D estimates (vs. Accept an Offer)	No Page		
	Prime Central		
	KMB/KMM		
	Remind Me Later		
	Other		

Note. Based on comparing usage in the 90-day window around cancellation entry (excluding the 5 days around the entry date).